

Mutah University
College of Graduate studies

An Enhanced Path Loss Model for Accurate Indoor Distance Estimation

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A thesis submitted to the College of Graduate Studies in partial fulfillment of the requirements for the Master's degree in Computer Science to the Department of Information Technology, University of Mutah.

Mutah University, 2016

الآراء الواردة في الرسالة الجامعية لا تعبر
بالضرورة عن وجهة نظر جامعة مؤتة

بسم الله الرحمن الرحيم



MUTAH UNIVERSITY

College of Graduate Studies

جامعة مؤتة

كلية الدراسات العليا

نموذج رقم (14)

قرار إجازة رسالة جامعية

تقرر إجازة الرسالة المقدمة من الطالبة وعد أمجد الشمايلة الموسومة بـ:

An Enhanced Path Loss Mode for Accurate Indoor Distance Entination

استكمالاً لمتطلبات الحصول على درجة الماجستير في الحاسوب.

القسم: تكنولوجيا المعلومات.

	التوقيع	التاريخ	
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د. احمد محمد العبادلة		26/4/2016	عضواً
د. مصطفى محمد حماد		26/4/2016	عضواً
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ACKNOWLEDGMENT

There are several people who help me in this thesis and without them, the thesis has not been done.

First, I am extremely thanks and grateful to my supervisor Dr. Mohammad AL Nabhan for his support, guidance, and valuable comments to complete this project. Second, I would like to thanks, Dr. Ahmad Abadleh for his advice and useful feedback.

All thanks and appreciation to my grandmother, my father, my mother, brothers, sisters and all people, who help me and stood by my side always, thanks for all.

Wa'ed Amjad AL-Shamaileh

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ABBREVIATIONS

LBS	Location Based Service
Wi-Fi	Wireless Fidelity
RSS	Received Signal Strength
AP	Access Point
LOS	Line of Sight
NLOS	Non- Line of Sight
PLM	Path Loss Model
PLE	Path Loss Exponent
POA	Phase of Arrival
RTOA	Roundtrip of Flight
TDOA	Time Difference of Arrival
TOA	Time of Arrival
IEEE	Institute of Electrical and Electronics Engineers
WLAN	Wireless Local Area Network
SSID	Service Set IDentifier (SSID)
BSSID	Basic Service Set IDentification (BSSID)
GPS	Global Positioning System
3D	Three-Dimensional
FSPL	Free Space Path Loss Model
FAF	Floor Attenuation Factor
WAF	Wall Attenuation Factor
UWB	Ultra-WideBend
ECEF	Earth-Centered Earth -Fixed
EDP	Energy of Direct Path
CSI	Channel State Information
WILL	Wireless Indoor Logical Localization
EKP	Extended Kalmen Filter
Li-Fi	Light Fidelity
MAC	Media Access Control
TOF	Time of Flight
ANDP	Angle of Direct Path
PDR	Pedestrian Dead Reckoning
KNN	K-Nearest Neighbor

Abstract

An Enhanced Path Loss Model for Accurate Indoor Distance Estimation

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Mutah University, 2016

Indoor localization based on received signal strength has become very popular in recent years. Wi-Fi radio signals are highly used to navigate and locate users in indoor environments. This is due to high availability of Wi-Fi technology within most buildings including; universities, hospitals, homes and companies. In addition, availability of smartphones and laptops equipped with Wi-Fi adapters has increased Wi-Fi popularity.

This work presents a new approach required to enhance distance estimation process using log-distance path loss model based on Wi-Fi RSS. The proposed approach relies on analyzing Path Loss Exponent (PLE) and Received Signal Strength (RSS) variables through a set of procedures allowing the optimal approximation of these variables. In addition, the proposed approach provides a best-fit relationship between these variables improving estimated distance accuracy within both in Line of Sight (LOS) and Non-Line of Sight (NLOS) cases.

The proposed approach consists of three main functional steps. The first step is responsible for measuring RSS values in different environmental settings. The second step includes approximating optimal PLE values and its relation to RSS and estimated distance accuracy. The outcomes of the second step are used to obtain optimal ranges of PLE values required for both LOS and NOLS environments. Obtaining these optimal values allows to remove errors and noise in RSS and reduces the effect of signal multi-path, allowing for enhanced distance estimation in the last step.

The proposed approach was experimentally tested and evaluated using a novel evaluation methodology representing all possible navigation environments. Several experimental scenarios were conducted measuring up-to-date and real-time signal strength measurements for mobile user in LOS and NLOS environments. Measurements were applied to the functional approach procedures following passive analysis and statistical methods to approximate new Path Loss Model (PLM) parameters. In addition, a comparison analysis study was carried between the proposed approach and conventional path loss models with reference to achieved distance accuracy. Results have confirmed the advancement of distance accuracy and position performance using the proposed approach in both LOS and NLOS environments. At a 95% confidence level, the significant difference between real distance and estimated distance was reduced using the proposed approach comparing to conventional models.

Keywords: LOS, NLOS, path loss model, path loss exponent, received signal strength

الملخص

تعزيز مسار نموذج الخسارة بتقدير دقيق للمسافة الداخلية

وعد امجد الشمايلة

جامعة مؤتة ، 2016

تحديد الموقع في الاماكن المغلقة بالاعتماد على قوة الاشارة المستلمة اصبحت منتشرة جدا فى السنوات الاخيرة. فالاشارات اللاسلكية Wi-Fi اصبحت تستخدم بدرجة كبيرة جدا وبهدف التعرف وتحديد المستخدمين فى بيئات الشبكة الداخلية المحلية. ويرجع ذلك الى توافر تقنية Wi-Fi فى معظم المبانى والتى تضم الجامعات والمستشفيات والمنازل والشركات. وبالاضافة الى ذلك، توفر اجهزة الكمبيوتر المحمولة، والهواتف الذكية، والمجهزة بخدمة Wi-Fi والتي ساعدت على زيادة انتشار استخدام شبكة Wi-Fi.

في هذا الدراسة، استخدم نهج جديد مقترح بهدف تعزيز عملية تقدير المسافة باستخدام (log-distance path loss model)، والتي تعتمد على (Wi-Fi RSS). وهذا النهج المقترح يعتمد على تحليل المتغيرات فقدان المسار الأسي (PLE) وقوة الأشارة المستقبلة (RSS) من خلال مجموعة من الإجراءات التي تسمح بالتقريب الأمثل لهذه المتغيرات. وبالإضافة إلى ذلك، يوفر النهج المقترح القدر لعلاقة تناسبيه بين هذه المتغيرات، لتحسين دقة المسافة الداخلية سواء كان ذلك في حالات (NLOS) & (LOS).

النهج الوظيفي المقترح يتكون من ثلاث خطوات رئيسية. الخطوة الأولى المسؤولة عن قياس قيم قوة الإشارات الواردة (RSS) في ظروف بيئية مختلفة. وتشمل الخطوة الثانية على التقارب الأمثل لقيم (PLE) وعلاقتها مع (RSS) ودقة المسافة المقدرة. وتستخدم نتائج الخطوة الثانية للحصول على نطاقات المثلى لقيم لمسار نموذج الخسارة (PLE) اللازمة لبيئات (NLOS) & (LOS). بعد ذلك، الحصول على القيم المثلى لهذه الأخطاء والضوضاء في (RSS) وإزالتها حيث يتم تقليل تأثير الإشارة للمسارات المتعدد والتخفيف من السماح لتقدير المسافة المعززة في الخطوة الثالثة.

ان النهج المقترح الذي تم اختباره تجريبيا وتقييمه باستخدام منهجية التقييم الاصلية والتي تمثل فحص جميع البيئات الممكنة. حيث أجريت قياسات من خلال عدة سيناريوهات تجريبية حديثة لقياس قوة الإشارة في الوقت الاني لمستخدم الهاتف المحمول في بيئات (LOS) & (NLOS). وبعد ذلك، طبقت القياسات إلى إجراءات النهج الوظيفي عقب التحليل السلبي والأساليب الإحصائية لتقريب عناصر جديدة لنموذج فقدان المسار (PLM). وبالإضافة إلى ذلك، أجريت دراسة تحليل مقارنة بين النهج المقترح والمسارات التقليدية لفقدان نماذج بالإشارة إلى تحقيق دقة المسافة. وقد أكدت النتائج على دقة المسافة وأداءها باستخدام النهج المقترح في بيئات (LOS) & (NLOS). لتحديد المواقع. وبمستوى ثقة بلغت 95%، وانخفض الفرق الكبير بين المسافة الحقيقية والمسافة المقدرة باستخدام النهج المقترح بالمقارنة بالنماذج التقليدية.

Chapter 1
Introduction

1.1 Motivation

The Global Positioning System (GPS) is considered one of the most widely used navigation technology for outdoor environments due to its high availability, simplicity, and performance. However, GPS is not the optimal navigation choice for indoor environments due to insufficient availability of GPS signals indoors required to locate users' position. Hence, the use of Wi-Fi technology has raised and considered the main technique for indoor localization because of its simple infrastructure and high availability. Distance metric between the transmitter (Access Point) and mobile user is considered the important factor in localization using Wi-Fi. Accordingly, the use of Wi-Fi navigation signals and path loss models is considered an important field to be investigated in order to provide improved models for enhanced distance estimation and increased localization performance.

1.2 Overview

Location Based Service (LBS) have attracted a lot of research attention in recent years. LBS utilizes users location to provide services to mobile users within in outdoor environment and indoor environments. Such services include security, tracking, and set of advertising applications (Schiller & Voisard, 2004). Indoor localization systems provide a new era of LBS services, in which users and objects are detected inside buildings.

Several technologies exist for in indoor localization systems including; Wi-Fi, Bluetooth, Cellular based, UWB (Ultra-Wideband) and others (Liu, Darabi, Banerjee, & Liu, 2007). Wi-Fi is one of the most technologies used within indoor buildings due to several reasons explained earlier. Wi-Fi positioning is based on several factors related to radio signal characteristics and used determine the location of users or objects. Some of these factors include Time of Arrival (TOA), Angle of Arrival (AOA), Received Signal Strength (RSS), Phase of Arrival (POA), Time Difference of Arrival (TDOA) and Roundtrip of Flight (RTOA). The RSS measure the power level of received signal and it suffers from server problem such multipath problem. This problem causes the attenuation and loss of Wi-Fi Radio signals. Multipath occurs when multiple reflected copies of signal reach the receiver from different paths. Multipath caused by diffraction, scattering, and reflection of signals. This result in increased signal travel time to reach the destination and consumes more power.

Reflection is a phenomenon for propagation mechanism occurring when electromagnetic wave strikes of flat or smooth surfaces. Radio signals are reflected in indoor by walls, floors, and other obstacles may

found in buildings. Diffraction phenomenon occurs when sharp objects found in the path between transmitter and receiver. However, waves, in this case, bend around obstacles within nonline of sight measurements. The obstacles can include furniture and large objects. The advanced phenomenon is scatting, which occur when electromagnetic waves strike on coarse surface or edge of the small surface. This phenomenon causes the initial wave to decompose in small pieces propagating through several directions.

Mainly, Wi-Fi indoor localization is based two approaches: fingerprinting and model based. The fingerprinting approach is empirical method realize on measuring RSS values in two phases: offline phase and online phase (So, Lee, Yoon, & Park, 2013). In offline, RSS values are recorded from the nearest access point (reference point) to build radio map of buildings. Furthermore, during online phase the user collects RSS from nearby access points and compares it with radio maps created to estimate users' location. Although, fingerprinting technique is considered an accurate method but need a lot of effort and time to build the radio map. In addition, it requires a continuous update to recorded RSS values when any change occurs to the environment.

On another hand, the model-based approach uses path loss propagation models to describe attenuation of the signal within distance. Path loss model is not needed radio maps to determine a location of the user, however, it's based on the mathematical relation between PLE and RSS to compute the distance. In which, RSS values from different access points and PLE values can convert to distance using path loss model.

1.3 Problem statement:

Distance estimation accuracy is an important metric to be considered for indoor localization performance. Path loss model is the main approach used to estimate the distance between AP and mobile user based on PLE and RSS parameters. PLE depends on propagation environment and rate of signal decays during distance increase. Hence, the environment is considered as rapid challenge causing inaccurate approximation of PLE. In addition, RSS is affected by obstacles inside buildings. Accordingly, determining optimal values of PLE and RSS is considered an important issue to be considered in order to achieve enhanced positioning accuracy indoors using path loss model solutions.

1.4 Aim and objectives:

This work presents a new functional approach enhancing the implementation of current Log-distance path loss model for increased positioning performance. The aim was to enhance distance estimation within indoor environments by precisely describing the relation between

navigation received signals strength (RSS), path loss exponent (PLE) values and distance estimation accuracy. The new framework describes a new functional approach for PLM parameters measurements and processing achieved the required accuracy. This work includes following objectives:

1. Understand Wi-Fi radio signal characteristic taking into consideration a set of propagation errors including attenuation of signal power and multipath.
2. Analyze and measure signal characteristic through a set of extensive experiments with a focus towards existing path loss model parameters.
3. Develop a new functional approach enhancing the approximation of optimal PLM variables during measurements allowing for increased distance estimation accuracy.
4. Define an experimental evaluation model used to validate the proposed functional approach within different navigation and measurement environments. This evaluation model describes the relation between RSS, PLE and estimated distance values. In addition, the evaluation model validates the capability of the proposed framework in achieving the required distance accuracy.
5. Analyze and compare achieved distance accuracy levels between proposed framework and conventional PLM approaches using statistical methods.

1.5 Contribution of thesis

This work presents an advancement to Wi-Fi indoor navigation performance. This was achieved by providing a new functional approach enhancing the implementation of conventional path loss models while estimating mobile users' distances.

1. Describe the relation between PLM components and estimated distance accuracy.
2. Provide a new method for PLM components estimation after decreasing the effect of multipath and signal errors. Optimal PLM components were estimated within LOS and NLOS environments.
3. Describe a detailed novel evaluation model used for experimental measurements and analysis of PLM parameters, as well as distance accuracy assessment.

1.6 Structure of thesis

Chapter 2 presents literature survey about indoor positioning systems and techniques with a focus on path loss model. In addition, describes the 2.2 Theoretical background. However, Theoretical background illustrates indoor localization techniques, android platforms,

indoor propagation models and smartphone sensors. Chapter 3 presents the proposed approach and functional approach.

The evaluation methodology, results analysis and conclusions are described in Chapter 4. Evaluation methodology describes details of experimental work conducted with a link to functional approach implementation and PLM parameters analysis and approximation. Results analysis section describes and analysis, experimental testing results and presents a statistical comparison between proposed approach and conventional PLM models with reference to distance accuracy. Conclusions concludes this work and provides important recommendations for future work.

Chapter 2
Literature Review and Theoretical Background

2.1 Literature review
2.1.1Overview

Indoor positioning is achieved using several techniques providing information about the location of users and devices (Gu, Lo, & Niemegeers, 2009) (Yang & Shao, 2015) (Liu, Darabi, Banerjee, & Liu, 2007). Triangulation positioning algorithm uses geometric properties of the triangle to determine a location using distance or angle. Angle estimation uses Angle of Arrival (AOA) for received signal to estimate locations by determining the intersection point of angle direction line from at least two references (Niculescu & Nath, 2003).

Active Badge system one of the oldest systems that utilize infrared technology for localization (Liu, Darabi, Banerjee, & Liu, 2007). Position information is achieved from unique IR signal sent from a badge worn by users. The signals received by sensors equipped in rooms with known location. In (Chen, Lymberopoulos, Liu, & Priyantha, 2013) an additional indoor positioning approach was proposed using FM radio signals. This approach is based on the increase of wireless signature during the combination between RSSI and physical layer information. The physical layer information includes multipath, signal-to-noise ratio, and Frequency offset. The Ultra-Wideband (UWB) was used in (Ghassemzadeh, Greenstein, Kavcic, Sveinsson, & Tarokh, 2003) in both residential and commercial buildings localization. In this work, a statistical model of path loss model is presented, considering two environment categories Line of Sight (LOS) and None Line of Sight (NLOS). Path loss parameters derived from experimental results confirmed with simulation results.

Distance estimation is one of the most metrics used in indoor localization. Wi-Fi Trilateration technique uses a distance metric of at least three references points to locate intersection point between three Access Points' (AP) coverage circles. In (Ilci, Gulal, Alkan, & Cizmeci, 2015) Wi-Fi based indoor localization uses Trilateration to estimate the position of the mobile device in the line of sight. Trilateration technique depends on two steps. The first step is to estimate a distance between four APs and mobile device. It uses Received Signal Strength (RSS) from AP in path loss model to estimate a distance. In the second step, the estimated distance is used to determine a location by the intersection point of four access points. As recorded in this paper, the achieved accuracy of this system is between 1.3 m to 8.6 m in an indoor environment.

GPS with Wi-Fi have been used in one system to locate a user position in everywhere and any environments (Saengwongwanich, XIU, WENG, & Boonsrimuang, 2014). GPS technique uses the Earth-Centered

Earth-Fixed (ECEF) technique and a set of orbital satellites to estimate location. However, Wi-Fi fingerprinting uses the RSSI values from several APs. Moreover, for integrated positioning solution, KNN (K-Nearest Neighbor) algorithm, and Gaussian probability density functions are used for position information matching and enhancement phases. As a result, a combination of data received from the geographic coordinate system (GPS), fingerprinting technique and path loss model are used to estimate accurate location information.

Wireless Indoor Logical Localization (WILL) approach was presented in (Wu, Yang, Liu, & Xi, 2013). This system determines user location without a set of survey procedures. The main idea of WILL is to build floor plan of the user by controlling motion using mobile phone and unexploited RF signal characteristic. However, this approach consists of two phases: training and serving. The achieved room accuracy using WILL room was 86%.

Sen at el, presented CUPID system able to avoid the effect of multipath reflections by utilizing physical layer information allowing accurate estimation of distance and angle of mobile devices (Sen, Lee, Kim, & Congdon, 2013). In addition, CUPID uses AOA with user mobility to estimate Angle of Direct Path (ANDP). In CUPID Channel State Information (CSI) exported from physical layer components was used to estimate Energy of Direct Path (EDP). EDP gives a reliable indicator of distance using path loss model. In the same concern, (Mariakakis, Sen, Lee, & Kim, 2014) presents a new system known as SAIL to improve location accuracy and solve shadowing problem in CUPID. SAIL depends on distance, dead-reckoning technique and geometric method to estimate user location. This system uses a delay of signal propagation to estimate a distance between AP and mobile client. Furthermore, to eliminate multipath reflection effects on Time of Flight (TOF), SAIL makes integration between the physical layer and user mobility.

The radar system is a first indoor positioning system based on Wi-Fi signal strength to locate and track the user (Bahl & Padmanabhan, 2000). RADAR based on triangulation location technique with signal strength and signal to noise ratio. This paper describes two types of methods to identify user position. The empirical method depends on record signal strength on offline phase. It uses the nearest neighbor to determine allocation orientation of the user in matching process. The radio propagation method depends on Wall Attenuation Factor (WAF) and Floor Attenuation Factor (FAF) with path loss model, which WAF is a number of obstructions

Hybrid EKP method was described in (Torteeka, Chund, & Dongka, 2014,). This method improves accuracy and robustness in dynamic and noise indoor environments. This hybrid system is most robustness than other systems. It makes a combination between advantages of location

fingerprinting technique based on RSS, and WiFi trilateration technique based on RSS using Extended Kalmen Filter (EKF). The path loss model used in this system add a walls-loss factor to represent a sum of losses conducted by each wall and the Path Loss Exponent (PLE) used was between 2-6.

A hybrid system to estimate mobile device position using Wi-Fi and Li-Fi technologies is described in (Huang, Zhang, Ge, & Lu, 2016).This system depends on Li-Fi lamp with Wi-Fi access point to derive the PLM coefficients . This system works to detection the Li-Fi signal to compute the distance between Li-Fi lamp and an access point using buildings floor map. Afterward, calibrated coefficient to RSS is derived using path loss model. In the last step, user position is computed using calibrated coefficient and new RSS. Results described in this paper approve the efficiency of used path loss exponent and model to improve estimated distance. The achieved accuracy in this system was improved to 80%.

Additional methods have described enhancing path loss model for enhanced distance estimation. In (Bose & Foh, 2007) an empirical work was conducted to investigate the relation between RSS and distance estimation. After conducting series of experiments in several environments. Path Loss Exponent (PLE) values were predicted, result confirm that if RSS is strong than or equal to -49 then the PLE is 5, otherwise PLE was 4.In addition, distance estimation using path loss model described in (Mazuela, et al., 2008, May) becomes more precise by dynamically choosing PLE values. This method use RSS to estimate appropriate PLE that fit with attenuation of propagation signal between Mobile Station (MS) and BSs. The PLE values were compensated from 2 to 6. After that, PLE determination depends on the maximum compatibility of estimated distance.

In the same concern, a novel method of indoor localization was proposed in (Mazuelas, et al., 2009), which uses RSSI in real time to estimate distance. In addition, PLE was estimated in dynamic and low complexity environment from RSSI. Robust indoor positioning provided by real-time RSSI values in unmodified WLAN networks were considered. The PLE value was selected from a set of values in order to maximize the compatibility of the distance estimation. The result of this paper depends on unmodified WLAN network with a mean of error less than 4meters.

An adaptive path loss model estimating PLE based on node's known location, and RSS received from beacon node is described in (Park, Ahn, & Yu, 2008, January). In which, the value of PLE was used to estimate user's location within same space. This system provides a location accuracy reaching 2.5 m.

Salman, Ghogho, & Kemp, (2012) and Salman, Kemp, & Ghogho, (2012) present location estimation of the wireless device based on RSS and

unknown path loss model. Hence, the path loss exponents were estimated by assuming the incorrect value of PLE and study the effect of error value in the accuracy of location via simulation.

In (Chan & Sohn, 2012), indoor positioning accuracy was enhanced by combining two Wi-Fi positioning approaches; fingerprinting and trilateration. Fingerprinting matching depends on pre-recording of RSS. The second approach is distance estimation based on trilateration technique. It depends on RSS with path loss model using 4 as the value of PLE in all experiments.

In addition, an integrated solution for indoor localization was presented in (Chen, Zou, Jiang, Zhu, Soh, & Xie, 2015), in which Wi-Fi signaling, Smartphone, and landmark information were fused using Kalman filter to obtain an accurate position. Landmark include turns, elevators, escalators, and stairs. The landmark is a specific pattern that can be distinguished after reading sensors data. In Wi-Fi based approach, the weighted path loss algorithm is used with RSS to estimate location, and path loss model used to estimate distance. After that, the weight is determined by the inverse of distance, whereby the summation of the weighted location of routers used to locate a device. However, Pedestrian Dead Reckoning (PDR) is used to support determining the current position of user achieved from several sensors embedded in the mobile phone. The accuracy of PDR approach is improved,when using at the initial point of estimation.This fused system provides an average of position accuracy about 1m.

Self-estimation of PLE is proposed in wireless networks (Hu & Leus, 2014). This depends on linear regression model for path loss exponent. This model uses total least square method on collected RSS to estimate PLE values. Afterward, weighted total least square was used to decrease of estimation error and improves positioning performance.

2.1.2 Summery

Many research works have addressed indoor localization methods and technologies. However, still exist some drawbacks affecting achieved position accuracy within indoor environments. The main focus was on fingerprinting and path loss model methods. However, the fingerprinting technique needs a lot of effort and time to build radio map. In addition, the fingerprinting database needs to be continuously updated when the environment changes (adding or removing the furniture). Trilateration technique used distance estimation as metric to locate a user location. The computation of distance using path loss model with RSS is susceptible to multipath effects due to the influence of obstacles on propagation waves.

This work focused on enhancing the efficiency of path loss model in distance estimation by using a range of optimal PLE and RSS to

accommodate changes of navigation environment because the environment is rapidly changing. A new approach was proposed allowing for the approximation of PLE ranges and decreases signal errors effecting received signal strength. The proposed approach also integrates navigation information from previous user step including RSS and PLE in the computation of position in the next user step.

2.2 Theoretical background

This section provides an overview of a set of localization technologies used indoor and outdoor positioning systems including; Wi-Fi technology and GPS. In addition, details of path loss models and android platform are also described.

2.2.1 Localization technology:

Several technologies have been used in to locate mobile users within a different environment. Global Positioning System (GPS) is positioning system widely used for outdoor environments. In the contrast, Wi-Fi is very used for indoor localization. The following sections describe both these technologies:

2.2.1.1 Wi-Fi technology:

Wi-Fi (Wireless Fidelity) is Wireless Local Area Network (WLAN) providing wireless network connectivity in a local distance range to devices such as personal computers and smartphone. Allowing internet access via a wireless network access points distributed at known locations and clear to users. Wi-Fi is also follows IEEE 802.11 standard (IEEE_802.11, 2016).

To obtain communication access to Wi-Fi network, the device should contain a wireless adapter configured to receive signals from the nearest access point. Wireless adapter converts the data sent into a radio signal and transmits it via its internal antenna. Afterward, the wireless router will receive the signal and decode it to be sent through the internet using wired Ethernet connection. This process is provided in the reverse way, which wireless router receives the signal and encodes it after that send the signal to wireless device adapters (Varma, 2012)

There are two scanning methods allowing devices to connect to the access point. During an active scan, the client device sends probe request frame via a wireless medium to any access point near to it. Then the device waits for probe response frame from the access point. The device can use the information in the probe response frame to connect with the access point and access to the internet. In the passive scan, the access point sends

a beacon frame periodically via a wireless medium. After that, the device can use information in beacon frame to connect with the internet.

A beacon frame is one WLAN frame that contains all information about the network. An Access point is broadcasting a beacon in periodical intervals; usually each 100 milliseconds. Table 2.1 shows part of the beacon frame body with a description of each field.

Table 2.1

Part of beacon frame body (Gerasenko, Joshi, Rayaprolu, Ponnavaikko, & Agrawal, 2001)

Beacon Frame Body Field	Description
Timestamp	Allows synchronization where station changes it local clock to the time of AP.
Service Set Identifier (SSID)	Name of the wireless network
Basic Service Set Identifier (BSSID)	MAC address of access point
Received Signal Strength (RSS)	Level of received signal
Beacon interval	Time interval between beacon Transmissions

IEEE 802.11 standard is wireless standard uses "over the air" interface to provide communication between access point or base station and the wireless client. In addition, IEEE 802.11 standard is a combination between physical layer and Media Access Control (MAC) layer specifications to investigate wireless local area network provide wireless communication in a different band. Tables 2.2 illustrate some IEEE standards with information of each one.

Tables 2.2

Some IEEE standards (IEEE_802.11, 2016)

standards	Year	Data rate(Mbit/s)	Approximate Rang	
			Indoor(m)	Outdoor(m)
a	1999	6, 9, 12, 18, 24, 36, 48, 54	35	120
b	1999	1, 2, 5.5, 11	35	140
g	2003	6, 9, 12, 18, 24, 36, 48, 54	38	140
n	2009	7.2, 14.4, 21.7, 28.9, 43.3, 57.8, 65, 72.2	80	250
ac	2013	7.2, 14.4, 21.7, 28.9, 43.3, 57.8, 65, 72.2, 86.7, 96.3	35	-
ad	2013	Up to 6,912	60	100

Wi-Fi Received Signal Strength (RSS) is very perverseness in indoor localization systems. Wi-Fi RSS is available in most buildings and does not need additional hardware to detect or access it. Therefore, the signal received can convert to distance using path loss model. In addition, some of the systems used the timestamp to know Time of Arrival (TOA) of the signal, which can be used to calculate the distance between user and access point.

A lot of challenges are facing the implementation of Wi-Fi RSS. This includes signal attenuation, reflection, diffraction and scatting. Multipath is a major issue, in which, the signal received by the receiver is a combination of the direct and reflected signal. These problems degrade the accuracy of systems depending on RSS to estimate the location of the user.

Although of this challenge can face the Wi-Fi, but it appropriates to use in localization systems. The reasons are the availability of Wi-Fi, which the access points are pervasiveness in the most building. Also, the most devices are equipped with a Wi-Fi adapter such the laptops, smartphone and others.

2.2.1.2 GPS technology

Global Positioning System (GPS) is a satellite-based navigation system. It uses radio signals received from orbital satellites to provide location, status, and time information for ground GPS receivers in different environmental conditions. The GPS was proposed for military use but later became available for civilian use (The Global Positioning System, 2016).

GPS consists of three main segments: a space segment (satellites), a control segment and user segment. The space segment is set of 24 satellites operating in 6 orbits, each satellite circle around the earth twice every 24 hours. The satellite structure arranged in a way, in which 6 satellites are available to every place on earth surface. The GPS satellite sends navigation messages in a continuous time, each message contains information including, the time the message was sent, the status of satellite and orbit information for satellites. Such information is used by GPS receivers to compute its location and speed. The control segment consists of the control station and monitor antenna used to monitor the status of satellites and correct navigation problems occurring. The user segment consists of military GPS receivers using the precise positioning service and civilian users using standard positioning service. The GPS receiver receives a signal from satellites and uses the transmitted information to calculate and determination a position of users and speed (Microsoft Research, 2016) (Kaplan & Hegarty, 2005).

GPS uses geometry information to predict a correct user position. The difference between satellite transmitted signal time and time of received signal on GPS receiver is used to calculate the distance to satellites. The distance is computed by multiplying the time difference by the speed of light. The distance between GPS receiver and at least four satellites is used to determine an intersection point using trilateration technique. The intersection point represents the 3D location of the user.

Although GPS provide an accurate and reliable position in the outdoor environment, but the signal may be degraded due to environmental effects and induced errors providing inaccurate location information. There are many of factors affecting the quality of navigation information such as; atmospheric effects, signal multipath or blocking, clock and computing errors. The signal multipath occurs when GPS signals are reflected by walls, tall building or other obstacles increasing the time required by signal to reach the ground receiver. An additional error source is caused by electronic interference and terrains which block the signal availability and prevent it from reaching the receiver.

The Figure 2.1 in below presents the some problem that effect in GPS signal. The GPS signal may face large building or any obstacles prevent the signal reach to the receiver. In addition, the signal may reflect and talk more time until reach to reach the receiver. All these problems effect in GPS accuracy. However the precision of GPS almost 5 meters (The Global Positioning System, 2016).

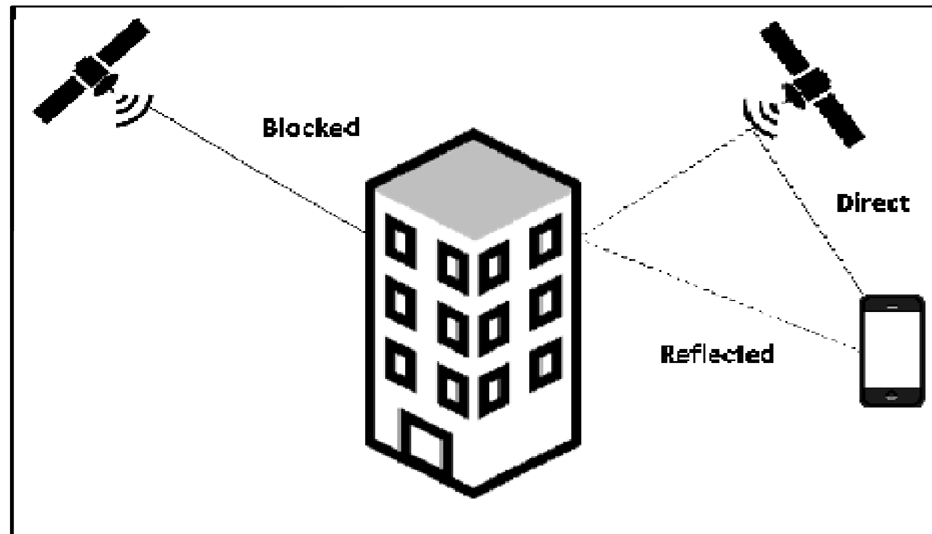


Figure 2.1
Some of the GPS signal problems

It is worth mentioning that a combination between GPS and Wi-Fi technology exist achieving high availability of location in anywhere and everywhere. The system in (Saengwongwanich, XIU, WENG, & Boonsrimuang, 2014)is indoor/outdoor system, which provides the location of the user in both environments. This system uses GPS if the number of available satellites is least four. Otherwise, the system switches to receive data from access points. In addition, life map system described in (Chon & Cha, 2011), tracks the user by fusing Wi-Fi, GPS and navigation sensors. The life map system is navigation the user in daily life.

2.2.2 Android operating platform

Android is operating system for mobile devices developed and managed by Google Inc (Android operating system, 2016) .It is an open source system which allows developers to access its source code for modification and development. Android OS consists of different layers, where each layer provides set of services to layers above it. All these layers together create OS, application and middleware. Android layers are described as follows:

1. ***Application***: this layer is the highest layer level, which allows developers or third party to install its required application.
2. ***Application Framework***: this layer provides high-level blocks to help to build the structure of an application for android OS.
3. ***Android Runtime***: this layer consists of two components. The first is the core libraries and is responsible for providing most functionalities in java core libraries. The second is a virtual machine called Dalvik Virtual Machine. Dalvik VM provides translation

between application side and operating side. In addition, it allows each android application to run in the separate process.

4. ***Libraries:*** it the next layer of Linux Kernel and written in C/C++ language. There are a set of libraries in this layer including SQLite database to share and store the application data, SS libraries for internet security and others of liberalities.
5. ***Linux Kernel***: it is a basic layer residing on top all android OS. In addition, it provides an abstraction between hardware and software layers. In addition, it provides a set of basic functionalities such as; memory management, process management, and device management.

Figure 2.2 illustrate architecture diagram of the android operating system.



Figure 2.2

Android operating system architecture (Android Architecture, 2016)

As explained in Chapter 4, this work utilizes a smartphone device running android platform and a sniffer application to read and measure RSS values.

2.2.3 Indoor propagation models:

2.2.3.1 Free Space Path Loss Model (FSPL)

This model is used in free space environments when the line of sight exists between transmitter and receiver. Moreover, there are no obstacles or objects causing signals attenuation or reflect. The FSPL model is denoted as follows (Bose & Foh, 2007):

$$PL(d) = -10log\left[\frac{G_t G_r{}^2}{(4\pi)^2 d^2}\right] \quad (1)$$

Where $G_t G_r$ are antennas gain of transmitter and receiver, respectively. ⍰ is wavelength in meter, d is distance between transmitter and receiver in meter.

2.2.3.2 Log - Distance Path Loss

This model presents the relation between received signal strength and distance in a logarithmic format. This path loss model is given by the following equation (Anthony & Okonkwo Obikwelu, 2014):

$$PL(d) = P_0 + 10\, n \log\left(\frac{d}{d_0}\right) \quad (2)$$

Where PL is path loss in decibel. $P_0$is path loss at $d_0$where d_0 is the reference distance in meter, and n is path loss exponent.

2.2.3.3 Log-Normal Shadowing

The log-normal shadowing model is similar to the model described in 2.2.3.2, with an additional random variable representing shadowing effect. The shadowing effect causes by different cutler between transmitter and receiver. This model is denoted as follows (Zhao, Li, & Shi, 2010):

$$PL(d) = P_0 + 10\, n \log\left(\frac{d}{d_0}\right) + X_\sigma \quad (3)$$

WhereX_σ is Gaussian random variable with zero mean, and σ standard in decibel.

2.2.3. 4 Log Distance Path Loss Model with Attenuation Factor

This is a log path loss model with additional factors. These factors are Wall Attenuation Factor (WAF) and a Floor Attenuation Factor (FAF). The following equation describes this model (Bahl & Padmanabhan, 2000):

$$PL(d) = P_0 + 10\, n \log\left(\frac{d}{d_0}\right) + FAF \quad (4)$$

Where FAF is the number of floors between transmitter and receiver. FAF values can be computed empirically.

After broad considering of all indoor spread models, log-distance way Path Loss Model was utilized as a part of this work to assess a distance. Log-distance way Path Loss model is a fitting model to appraise the distance between access point and portable client for a few reasons.

In the first place, it appropriates in all environments and does not require expansion data such shadowing, FAF, and WAF, it needs RSS readings and PLE values. Second, the shadowing parameter in Log-typical shadowing way PLM, WAF and FAF parameter were utilized as a part of particular situations, which not suitable to use in all situations. In the last, the FSPL needs to culminate LOS case amongst transmitter and receiver and does not require obstructions can impact on the sign.

Wherefore, the log-distance way Path Loss Model is proper for various situations and does not require extra data aside from RSS and PLE.

2.2.4 Smartphone sensors

Smartphone inertial sensors are given another significance of limitation frameworks. The sensors in Smartphone empower to decide a separation of clients, find, and following of the client. There are a few of sensors utilized as a part of confinement framework. Accelerometer, whirligig, and magnetometer are some of these sensors (Bo, Li, Jung, and Mao, 2013).

1. Accelerometer: Smartphone accelerometer is an advanced Accelerometer measure the correct increasing speed of the device, which the speeding up speaks to the adjustment in speed separated by time. In any case, the Accelerometer can use to recognize a movement of the client and figure out whether a client moving or stationary.
2. Gyroscope: the spinner sensor uses to decide the introduction. Gyroscope alone does insufficient to give exact development, so the accelerometer is consolidated with the Gyroscope. This joined permit to adjust the commotion data can happen in accelerometer perusing.
3. Magnetometer: the magnetometer used to determine the quality, bearing, or both in light of earth attractive field. The magnetometer can partition into two fundamental sorts: vector magnetometer uses to determine the heading. Second, a scalar magnetometer that measures the cumulative quality of the attractive field.

The smartphone sensors can use with another framework to find and following the client. The circuit between Wi-Fi innovation, sensors, and points of interest has been utilized to get precise position client (Chen, Zou, Jiang, Zhu, Soh, and Xie, 2015). The life map utilizes smartphone

sensor such accelerometer and gyrator with Wi-Fi to track the client (Chon and Cha, 2011).

2.2.5 Summery

In this chapter, which is to be had a notion of a few themes. To begin with, present Wi-Fi innovation, which it utilized as a part of this work to process a distance utilizing Received Signal Strength (RSS). What's more, depicted GPS innovation, which it utilized as a part of an outdoor environment instead of indoor situations. Second, depicted the android working framework. Android it utilized as a working framework as a part of the Smartphone of trials. Additionally, it used to actualize an application con read RSS values from AP. Third, demonstrated the engendering models of way Path Loss. Log-distance Path Loss model was utilized to evaluate a distance in this work since it appropriates to the test environment. In the last, Smartphone sensor was represented to decide a distance and area of the client utilizing Smartphone sensors.

Chapter 3
Proposed Model Design and Functional Approach

3.1Proposed functional approach

Through investigation of conventional path loss models, it was clear that Wi-Fi signals quality are degraded within indoor navigation environments due to several factors. These factors affect the precision and accuracy of distance estimation. The multipath problem is one of the main factors in which received signal is a combination of direct as well as reflected signals. Path loss is another factor in which the signal attenuates over distance.

Path Loss Exponent (PLE) is a basis parameter in path loss model, used along with Received Signal Strength (RSS) to estimate a distance. PLE represents signal propagation environment and it describes signal attenuation while the distance between user and access point is increased. Hence, no current constant value of PLE exists to represent propagation environments. Therefore, choosing the appropriate and approximate value of PLE is an important task to be considered. However, normal values of PLE in LOS environment like corridor will be close to 2, but in NLOS the value will be close to 4 (Sen, Lee, Kim, & Congdon, 2013). However, in some indoor conditions, PLE can be in the range between 4 to 6. Also, in other indoor environments such long tunnels PLE become less than 2.

In addition, RSS measures signal's power that is received from a source (AP). However, as explained before, transmitted signals may face obstacles causing, the signal to reach the receiver via multipath (multipath phenomenon). Accordingly, in this work distance is estimated using path loss model, after defining the relation between computed distance and RSS. In addition, PLE values will be chooses to fit the environment. This was achieved through a framework used towards decreasing the effect of multipath errors on distance estimation accuracy.

The first step of this work involves studying and investigating the characteristics of navigation radio signals through extensive experimental trials and mathematical inductions, with a focus toward enhancing current PLM implementation. Wi-Fi signals strength was measurement and logged within indoor environments using the mobile experimental setting (described in Chapter 4).

The conducted experiments were responsible for studying path loss model components. Therefore, the behavior of PLE parameter and RSS with and navigation environments with reference to distance is analyzed. Details of the experimental scenarios are described in next chapter.

The functional approach used in this work was divided into three interconnected steps as described in Figure 3.1. The first step described as *data collection and smoothing* which is considered as the key step in

proposed methodology. This step involves measurement of RSS values in different distance ranges from the access point and within LOS and NLOS environments. In addition, this step involves smoothing RSS measurements to decrease multipath errors.

The second step is described as *PLE analysis*, which encompasses the analysis of PLE values using the conventional path loss models to determine optimal PLE depending on average values of RSS. In addition, an attempt to study the relationship between estimated distance and optimal PLE value is considered in this step. After that, optimal ranges of PLE values are determined with regard to navigation environments providing accurate distance estimation.

The outcomes of this step will help to improve distance estimation using PLE ranges. The last step studies the relation between the computed distance and RSS values to measure the influence of RSS on estimated distance accuracy. The use of this approach attempts to reduce the effect of multipath on signals by using more consistency RSS and optimal PLE values.

Figure 3.1 demonstrate steps of proposed functional approach. Each step consists of several procedures described:

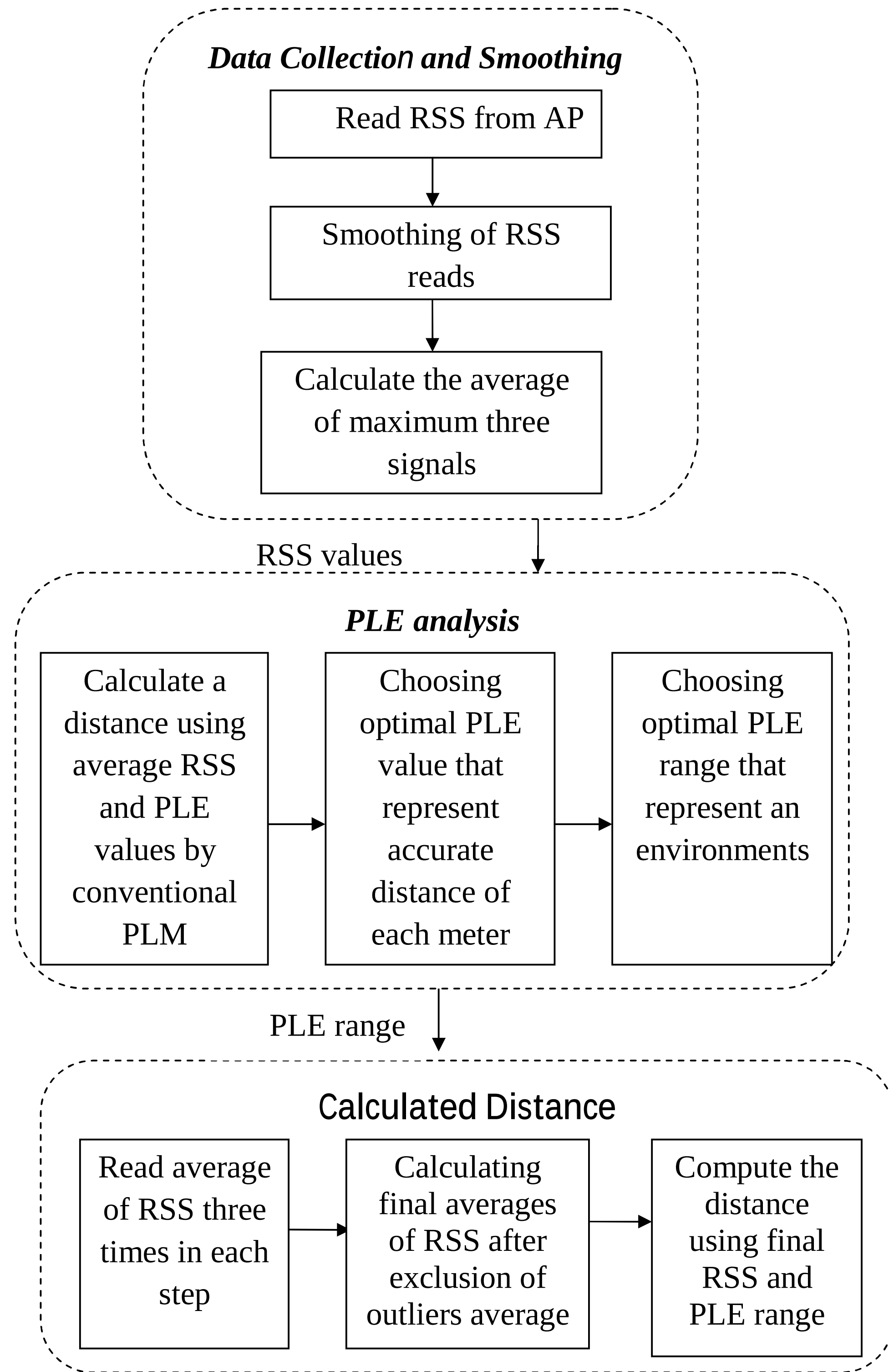


Figure 3.1
Proposed functional approach

3.1.1 Data collection and smoothing:

This step is required to provide up-to-date and real-time signal strength measurements for the mobile user. This is a measurement and a pre-processing step, in which all data is analyzed to understand features of signals used for navigation and distance estimation. Moreover, this step provides a clear understanding of environmental effects on signal quality readings. As explained in Chapter 4, this step is implemented using experimental scenarios within different environmental settings and conditions. Procedures conducted within this measurement steps are illustrated in details as follows:

A. Reading Received Signal Strength (RSS)

As a previously mentioned, RSS measurements might be different even in the same location because signals are susceptible to reflect, refract and scatting. For this reason, reading one value of RSS in the same location is considered unrealistic. Consequently, during experiments, RSS values were fetched several times (more than 5) for each meter (distance between the mobile device and specific access point). RSS readings were obtained in the range between 1m to 20meters within two environmental cases LOS and NLOS. In addition, RSS experiment was conducted in different time periods and repeated several times.

The Wi-Fi access point broadcasts a special frame called beacon frame every 100 milliseconds. The beacon frame contains the RSS value, timestamp, and MAC address. Our approach fetches the received beacons for a time window of one second. The ideal case is to receive 10 beacons everyone time window, but during our experiments, the number of received beacons were about 5 beacons. The missed beacons happened due to the effect of multipath. Based on that, our approach computes the average of the received beacons everyone time window, which means 5 RSS values.

Figure 3.2 illustrates mechanism used for data collection.

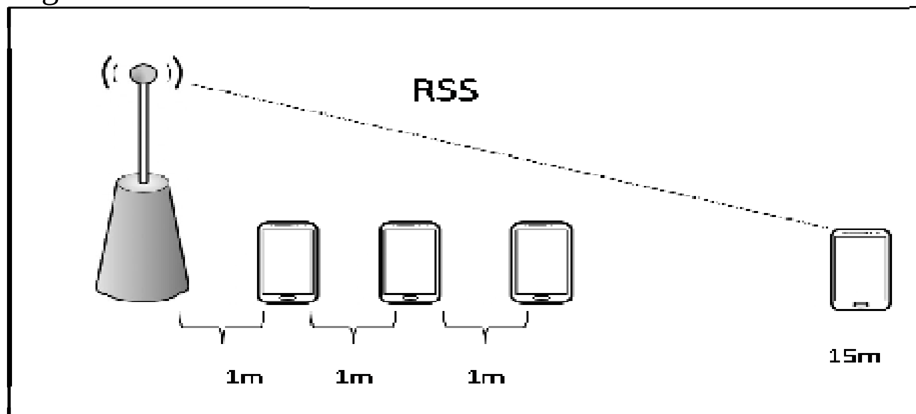


Figure 3.2
How to read RSS from

B. Smoothing RSS readings

After reading RSS values, some signals were considered as multipath signals. Hence, RSS values for these signals were removed and not considered when calculating the average of RSS values through excluded the extreme value. In this step, maximum, minimum, and median of RSS values are computed. Afterward, outlier values of RSS are removed when the difference value between median RSS and measured RSS value is greater than mid-difference value between maximum RSS and minimum RSS as form (Abadleh, 2015):

$$(|Median - RSS|) > (|Max - Min|)/2 \qquad (5)$$

This smoothing equation was utilized to evacuate exception estimations of RSS. It was picked because of its similarity with trial estimations. For instance, information gathered in this work was not extensive (just about 5 readings of RSS or less), which is reasonable for this equation. Second, this equation thinks about the connection between max, min, and middle qualities. Along these lines, barred quality is either max or min values, and a long way from the middle. This equation is connected to RSS values and demonstrated the legitimacy in picked exception values.

There are strategies have been utilized to smooth the information, which expels the anomaly from the dataset. Z-score and box plot are some of these techniques (Detection of Outliers, 2016).

C. Calculate average RSS:

This procedure is responsible for computing average of RSS readings after excluding outlier values making data more consistent and more factual. The maximum three RSS values are used to compute the average. This selection was made after initial experimental analysis confirming that maximum signal may give a good indicator of approximate RSS value. For this, take maximum three values can give accurate value because the signal of direct path is the highest value. In addition, in the worst case of the smoothing process the maximum outliers are two, so a remain values of RSS is three as maximum values.

Tables 3.1 and 3.2 describe examples of RSS values after smoothing within LOS and NLOS at five meters distance. The average of maximum three RSS values after smoothing is also described.

Table 3.1
RSS readings in LOS

RSS	Median	Max	Min	|Max-Min|/2	|Median-RSS|	
-59	-59	-55	-67	6	0	
-55	-59	-55	-67	6	4	
-57	-59	-55	-67	6	2	
-63	-59	-55	-67	6	4	
-67	**-59**	**-55**	**-67**	**6**	**8**	**Removed**

Average = (-55-57-59)/3=-57

Table 3.2
RSS readings in NLOS

RSS	Median	Max	Min	|Max-Min|/2	|Median-RSS|	
-51	-51	-49	-55	3	0	
-55	**-51**	**-49**	**-55**	**3**	**4**	**Remove**
-49	-51	-49	-55	3	2	
-50	-51	-49	-55	3	1	
-53	-51	-49	-55	3	2	

Average = (-49-50-51)/3=-50

4.1.2 PLE analysis

This step uses an average of RSS computed from the previous step to study the influence of PLE values on estimated distance. In addition, it illustrates how to choose appropriate PLE that fit within navigation environments of signals improving the accuracy of estimated distance. Log–distance path loss model was used in this step to compute the distance between transmitter and receiver. The log–distance path loss model used in (Sen, Lee, Kim, & Congdon, 2013) (Mao, Anderson, & Fidan, 2007) (Huang, Zhang, Ge, & Lu, 2016):

$$P_R = P_0 - 10\gamma \log(d) \tag{6}$$

Where P_R is received signal strength in dBm at receiver, P_0 is received signal strength at distance 1m from transmitter in dBm, d is distance between transmitter and receiver in meters; and γ is the path loss exponent. Alternatively the distance can expressed as:

$$d = 10^{\frac{P_0 - P_R}{10*\gamma}} \quad (7)$$

During ***PLE analysis phase*** optimal PLE with reference to average RSS values are obtained providing accurate distance estimation. Log-distance path loss model (described in equation 2) is used to calculate the distance between specific access point and mobile phone using average RSS values. Values of PLE was in range 2 to 3 in LOS, and in NLOS was in range 3 to 4. Following , optimal PLE values are selected based on investigating the relation between PLE range values, estimated distance accuracy and the real reference distance. Table 3.3 presents samples of approximated optimal PLE values considering an average of RSS. This table also describes a round of estimated distance using average RSS and optimal PLE values at different distances.

Table 3.3

Sample of optimal PLE values in LOS

Real distance (meter)	Average RSS (dBm)	Optimal PLE	Estimated distance (meter)
1	-39	3	1
5	-54	2.6	5
10	-49	2	5
15	-64	2.4	15

Table 3.4

Sample of optimal PLE in NLOS

Real distance (meter)	Average RSS (dBm)	Optimal PLE	Estimated distance (meter)
1	-45	4	1
5	-64	3.1	5
10	-62	3	5
15	-69	3	8

As can be seen in Tables 3.3 and 3.4 the optimal PLE values are diverse even in the same environment. This variance depends on propagation environments which are rapidly changing. Thus, there is a need to include a new step to estimate a range of optimal PLE values

representing the navigation environment instead of approximating a single PLE value. Preliminary experimental results were analyzed and used to find optimal ranges of PLE values for each environment. The optimal PLE in a range in LOS is between 2 to 2.4, and between 2 to 3.3 in NLOS.

Using linear regression on initial experimental measurements, the relation between RSS, optimal PLE values, and estimated distance is obtained in this step. A strong relation appeared between RSS and estimated distance. Also, a week relation is obtained between RSS and PLE. This relationship was used in computing optimal a range of PLE as described in the following step.

3.1.3 Calculating distance

This step relies on studying the relation between RSS values and estimated distance. Understanding this relationship allows to decrease fluctuations of RSS values and excluded outlier values reducing distance accuracy.

During this step, a new method to estimate the distance between access point and mobile user is presented. The new method depends on PLE ranges obtained from the previous step and on the relationship between RSS and distance.

In general, the proposed method starts by taking three readings of average RSS in each meter. The average of RSS is used to predict RSS values in the following meter step. Any RSS value with large variations will be excluded. In addition, state and readings of RSS were used to determine required PLE ranges. After determining RSS values on each meter, the average of distances will be computed using optimal ranges of PLE.

As described in chapter 4, in NLOS case values of RSS are more fluctuated than LOS case, because no straight line between transmitter and receiver. In addition, the signal power is attenuated rapidly until reaching the receiver in NLOS.

Algorithm (1) and algorithm (2) describes the complete process of the proposed approach for computing the distance between AP and mobile.

Algorithm (1): Distance estimated in initial step

Function initial step

1. *Input RSS* A_{01}, A_{02}, A_{03}
2. *Output* A_0
3. *Max=Max* $(\boldsymbol{A_{01}}, \boldsymbol{A_{02}}, \boldsymbol{A_{03}})$
4. *Min=Min* $(\boldsymbol{A_{01}}, \boldsymbol{A_{02}}, \boldsymbol{A_{03}})$
5. *Median= Median* $(\boldsymbol{A_{01}}, \boldsymbol{A_{02}}, \boldsymbol{A_{03}})$
6. *For i=1 to 3*
7. *If* $(|Median-A_i| < |Max-Min|/2)$
8. A_0*=Compute avg*(A_i)
9. *End For*
10. *If RSS >-65 then*
11. $d_0 = 10^{\frac{RSS_0 - A_0}{10 * LOS\gamma}}$
12. *Else*
13. $d_0 = 10^{\frac{RSS_0 - A_0}{10 * NLOS\gamma}}$
14. *End if*
15. *End Function*

2. Algorithm (2): Distance estimated using proposed approach and initial step

Algorithm: Compute distance

16. *Function Initial step*
17. *Input: RSS* A_0 *at place1,* RSS_0
18. *RSS* A_1, A_2, A_3 *at place 2*
19. $LOS\gamma = [2\text{-}2.4]$, $NLOS\gamma = [2\text{-}3.3]$
20. *Output: distance*
21. *Max=Max* $(\boldsymbol{A_0}, \boldsymbol{A_1}, \boldsymbol{A_2}, \boldsymbol{A_3})$
22. *Min=Min* $(\boldsymbol{A_0}, \boldsymbol{A_1}, \boldsymbol{A_2}, \boldsymbol{A_3})$
23. *Median= Median* $(\boldsymbol{A_0}, \boldsymbol{A_1}, \boldsymbol{A_2}, \boldsymbol{A_3})$
24. *For i=0 to 3*
25. *If* $(|Median-A_i| < |Max-Min|/2)$
26. A_d *=Compute avg*(A_i)
27. *End If*
28. *End For*
29. *If RSS>-65 then*
30. $d_0 = 10^{\frac{RSS_0 - A_d}{10 * LOS\gamma}}$
31. *Else*
32. $d_0 = 10^{\frac{RSS_0 - A_d}{10 * NLOS\gamma}}$
33. *End If*

34. End Function

The first step in the function is to calculate the distance; for the initial step of the user as described in pseudo code of algorithm1. This step is conducted by reading three averages from RSS values. The average RSS is average of five RSS values. Afterward, outlier values from three computed average are removed as explained in the previous step using the equation (5) and compute new averages of RSS (lines 7 to 9 in algorithm 1).

Following, the distance is computed using a range of PLE values and new average taking into account LOS range or NLOS range, as described in algorithm 1, lines 10 to 13. Distance is computed between next step of the user and an access point. In which, three new averages of RSS values are computed taking in account one average of RSS achieved from the previous step of the user (lines 18 to 20 in algorithm 2).

Now four averages (three from the new location and one from the previous location) of RSS are obtained. Afterward, smoothing of RSS values are conducted (lines 21 to 25 in algorithm 2). In the last step, distance is computed using optimal PLE ranges and last RSS average. Distance averages are also computed. These steps are repeated while the mobile user is moving (lines 17 to 33 in algorithm 2).

To recognize LOS case and NLOS, the limit quality can be resolved the RSS qualities are peruses in LOS or NLOS. The edge quality is - 65, which if the normal RSS is not exactly - 65 the estimations of PLE extent from 2 to 2.4 generally the PLE range from 2 to 3.3. The limit qualities were resolved from broad analyses.

Accordingly using this approach, RSS values from previous step walk participates in choosing RSS in current step walk. Therefore, any fluctuating RSS value which is considered different comparing with another value was excluded. In addition, the average of RSS in each location was computed along with a range of optimal PLE. This results in more consistency and accurate distance estimation.

3.2 An Example of proposed approach

The following an example explain how to compute a distance using a proposed approach. The example shows computed distance of two of user steps. The example following the steps in algorithm 1 and algorithm 2.

The computed distance of initial moving (algorithm1) of the user move in LOS case from AP, where the average RSS is less than -65 thresholds. The following steps explain in bellow :

1. Read 3 average of RSS values (algorithm1) .

RSS1	RSS2	RSS3	RSS4	RSS5	Average
-53	-52	-56	-54	-48	-53
-59	-65	-55	-58	-52	-58
-60	-55	-58	-62	-65	-60

2. Extract the outlier values of three average of RSS using equation (5).

RSS	Median	Max	Min	|Max-Min|/2	|Median- RSS|	
-53	**-58**	**-53**	**-60**	**3.5**	**5**	**Remove**
-58	-58	-53	-60	3.5	0	
-60	-58	-53	-60	3.5	2	

3. Compute the average of RSS values after excluded outlier values.
   (-58-60)/2=-59

4. Compute the distance using PLE range and average in step 3.

PLE	Average RSS	Distance
2	-59	13
2.1	-59	15
2.2	-59	12
2.3	-59	10
2.4	-59	9

5. Compute the average of distances in step4.
   Distance ~ 12.

The second moving (second step) of the user is following the steps in algorithm 2. The algorithm 2 illustrate in bellow:

1. Read three averages of RSS values (algorithm 2).

RSS1	RSS2	RSS3	RSS4	RSS5	Average
-53	-51	-48	-49	-54	-51
-62	-60	-56	-54	-58	-58
-56	-66	-60	-68	-57	-61

2. Extract the outlier values of three average of RSS from step 1 and RSS from the initial moving of user using equation (5).

RSS	Median	Max	Min	|Max-Min|/2	|Median- RSS|	
-59	-58.5	-51	-61	5	0.5	
-51	**-58.5**	**-51**	**-61**	**5**	**7.5**	**Remove**
-58	-58.5	-51	-61	5	0.5	
-61	-58.5	-51	-61	5	2.5	

3. Compute the average of RSS values after excluded outlier values.
   (-59-58-61)/3= -59

4. Compute the distance using PLE range and average in step 3.

PLE	Average RSS	Distance
2	-59	13
2.1	-59	15
2.2	-59	12
2.3	-59	10
2.4	-59	9

5. Compute the average of distances in step4.
   Distance ~ 12.

3.3 Summery

This chapter depicts the proposed utilitarian methodology in points of interest. The proposed approach comprises of three fundamental parts; information accumulation and smoothing, PLE investigation and distance computation. These first two segments are in charge of exploring estimations of PLM parameters including PLE and RSS, contemplating the connections between these parameters and evaluated distance and finally giving ideal scopes of these qualities. Distance count part is in charge of assessing precise distance in light of ideal PLM parameter' values evaluated through the first two segments.

Proposed approach in the third step was accomplished. Proposed approaches endeavor to improve the distance estimation amid make RSS estimations of every progression of client impact in next stride of the client. In any case, this methodology makes RSS values more consistency and fewer vacillations.

Chapter 4
Evaluation Methodology, Results Analysis and Conclusions

4.1 Evaluation methodology

This section presents a novel evaluation methodology used to investigate current existing path loss model used to estimate mobile users distance within indoor navigation environments. In addition, this methodology follows the functional approach described in chapter 3, in order to develop a path loss model enhancing distance estimation and positioning performance. The core approach used was based on conducting extensive experiments measuring and analyzing Wi-Fi signal strength in different indoor navigation environments including Line of Sight (LOS) and None Line of Sight (NLOS). The basic path loss model parameters affecting distance estimation being considered were path loss exponents (PLE) and Received Signal Strength (RSS). The main objective of measurement analysis was to develop a new approach to optimally estimate these two parameters achieving enhanced distance estimation while navigating indoors.

Real-time signal measurements were analyzed in two phases after considering LOS and NLOS navigation environments. The first phase was based on statistically analyzing achieved measurements using linear regression methods to find the relation between RSS, PLE and estimated distance aiming to provide dynamic approximate and optimal path loss model parameters for each distance and the environment. The second phase follows a functional approach to enhance estimated distance based on ranges of PLE and RSS and depending results achieved from the first phase. In addition, the analysis in both phases considers LOS and NLOS environments. Afterward, a comparison between conventional and enhanced path loss model is performed in terms of achieved distance estimation performance.

This section describes the experimental scenarios conducted and the experimental setup including software and hardware tools being developed and utilized during signal measurements.

4.1.1 Experimental environment and settings:

As described earlier, experiments were conducted indoors within different environments considering different complexity and obstruction levels. Obstacles in this environment including, walls, floors, and humans walk in colliders. Experiments were mainly conducted inside the IT department at Mutah University and private home.

Experiments were conducted in two different scenarios s in order to fetch of navigation radio signals from access points and implement the proposed functional approach described in chapter 3. The first scenario is

conducted in LOS condition, where the user holds mobile phone facing access point and obtaining signal strength readings within different distances starting from 1 meter reaching to 15 meters from the access point. Similarly, the second scenario was conducted using same settings however in NLOS condition, were obstacles between the mobile device and access points exists. Figure 4.1 represent both experimental scenarios in (a) LOS and (b) NLOS respectively.

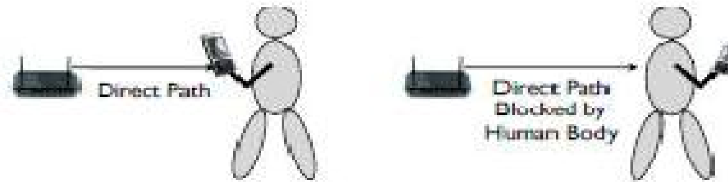


Figure 4.1: Experimental environment: (a) LOS scenario (b) NLOS scenario (Sen, Lee, Kim, & Congdon, 2013)

Hardware components used within experiments are described as follows:

- An android based Sony Xperia z1 smartphone, equipped with Wi-Fi.
- TP-Link access point, model ID is WR542G, MAC address is "0019E06ED27A", power is 9V and IEEE standard used is 802.11b.

Software components used within experiments are includes the following:

- An android application developed for the purpose of this work and used to read and investigate RSS values (see android appendix I).
- An off the shelf sniffer program known as (Wifi Analyzer) available for android devices, which was used to read RSS values in dBm).

4.1.2 Experimental scenarios and analysis phases

4.1.2.1 First experimental analysis: optimal PLE and RSS values

This phase aims to investigate the appropriate value of PLE and RSS variables achieving most accurate distance and measure the relationship between PLE, RSS and estimated distance. Detailed steps of this analysis phase are described below:

1. Read RSS for each meter in the range between 1m to 15m in two cases LOS and NLOS as described in the previous Chapter. Smooth collected data to exclude outlier values may not represent correct value of RSS.
2. Calculate average of highest three RSS values achieved from the previous step after smoothing process.
3. Calculate estimated distance using conventional path loss model described in (Chapter 3), and measure RSS values variation using all possible PLE values between (2 to3) in LOS case and values between (3 to 4) in NLOS for each RSS read.

4. Investigate results to measure the effect of PLE values on the accuracy of estimated distance.
5. Perform linear regression between PLE values and estimated the distance at each meter.
6. Perform an intersection between linear regression equation achieved from step (5) and reference distance equation to obtain optimal PLE values.
7. Conduct linear regression between average RSS values and optimal PLE values to measure the relationship between both variables.
8. Choose the optimal range of PLE values can represent the propagation environments of the signal in two cases LOS and NLOS.
9. Conduct linear regression between optimal RSS values and estimated distance values to measure the relationship between both variables.

The first scenario is essentially trying, which was led to think about customary way path loss model. The output of this analysis is PLE range. Figure 4.2 clarify the essential examinations in points of interest.

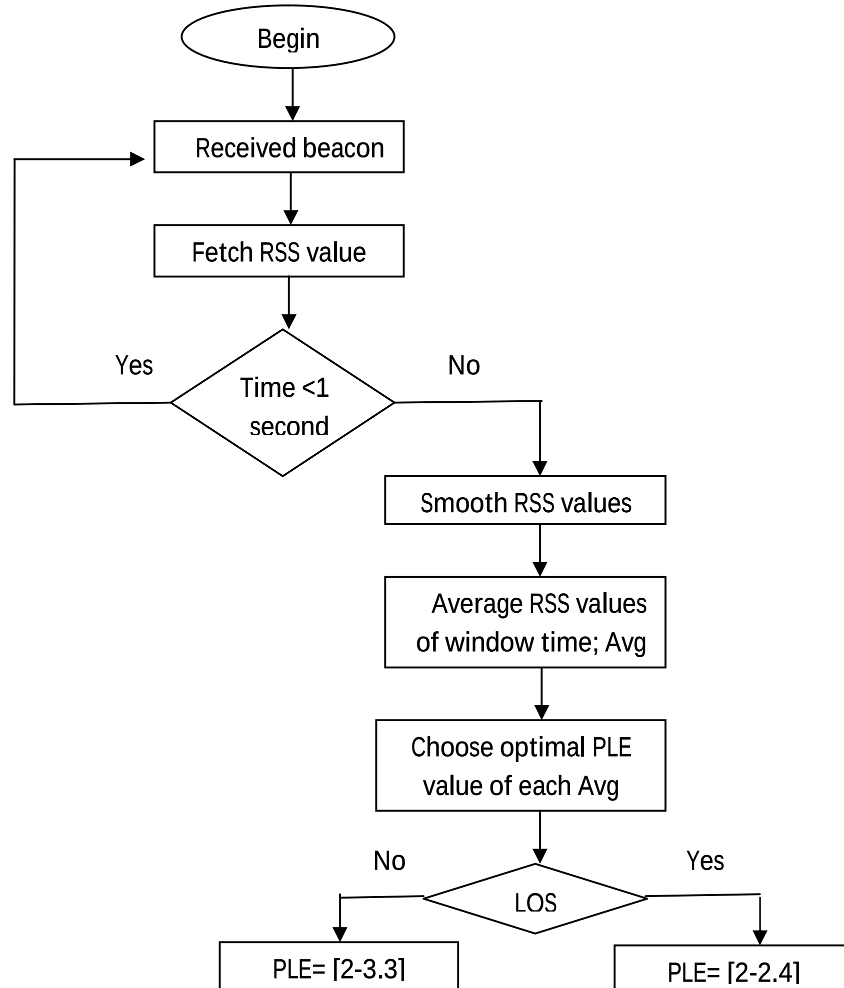


Figure 4.2
First scenario of experiments

4.1.2.2 Second experimental analysis phase: optimal PLE ranges and RSS

This phase aims to examine the accuracy of estimated distance using proposed approach. PLE range and average RSS are used with path loss model to evaluate of proposed approach. Detailed steps of this analysis phase are described as following:

1. Read an average of five readings RSS for each meter three times in two cases LOS and NLOS as described in the previous Chapter. Smooth collected data to exclude outlier average values may not represent correct value of RSS.
2. Calculate the last average RSS values achieved from the previous step after smoothing process.
3. Calculate estimated distance using conventional path loss model described in (Chapter 4), and measure Average of RSS values PLE range between (2 to 2.4) in LOS case and values between (2 to 3.3) in NLOS for each RSS read.
4. Calculate the average of distances of previous user step in one value represents the distance for the current user step. Repeat 1 -3 until users stop moving.

The second trial scenario was led to approve separation precision accomplished utilizing proposed approach. This approval relies on upon PLE ranges accomplished from the first test. Figure 4.3 presents the investigations of the second scenario.

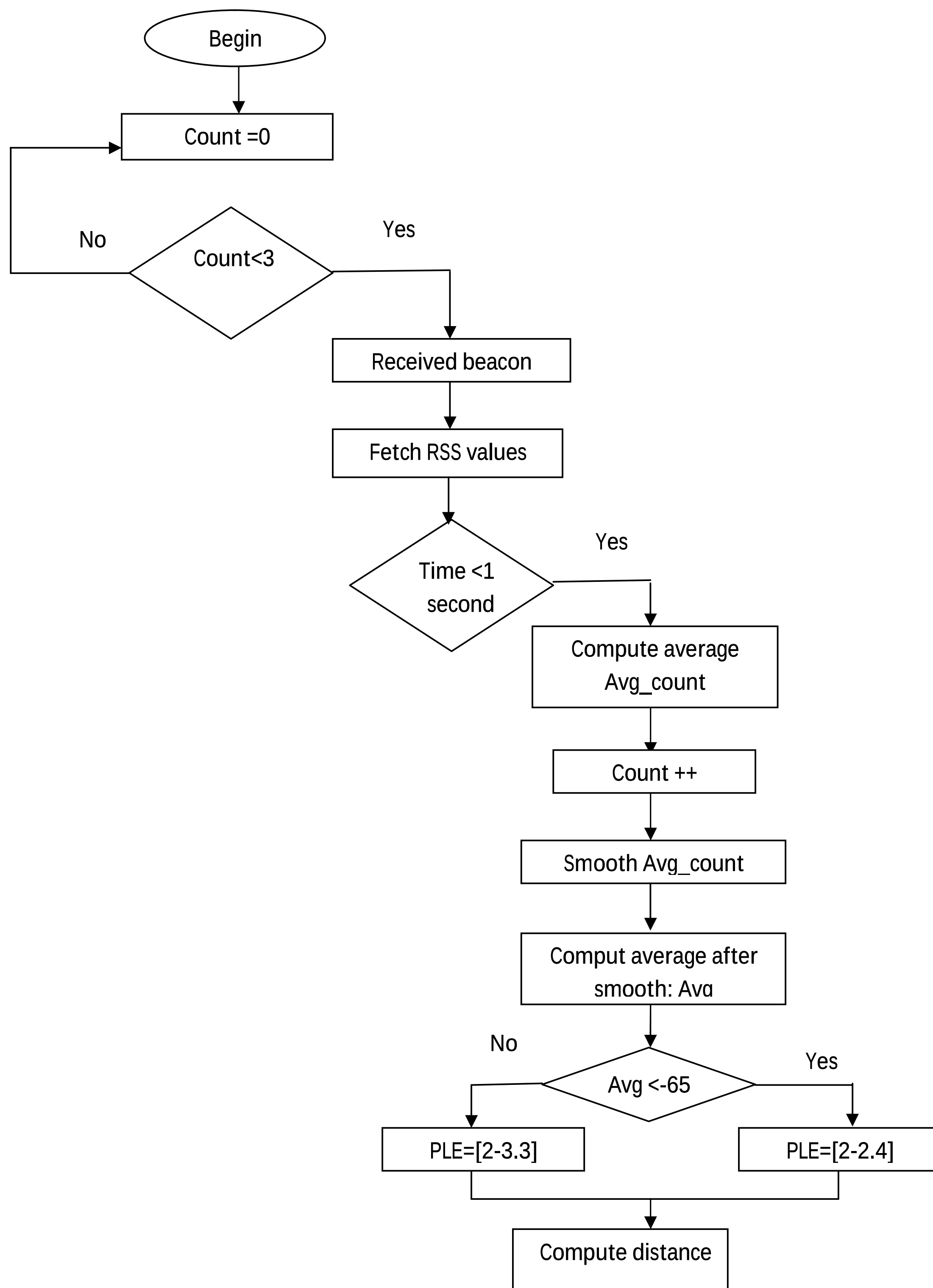


Figure 4.3
Second scenario of experiments

4.1.3 Summery

This chapter portrays the assessment technique utilized as a part of this work. This methodology depended on directing constant examinations, information estimations, and measurable investigation.

In which, two fundamental test scenarios were performed; the first is utilized to break down ordinary way Path Loss model parameters and concentrate relationship between these parameters to get ideal estimations of PLE. The second scenarios are utilized to look at the precision of assessed distance utilizing ideal PLM parameters evaluated from the previous scenarios and proposed approach.

4.2 Results analysis and discussion

This part presents and investigates results achieved from conducting the evaluation methodology described in previous section. Mainly, results were focused towards enhancing conventional path loss models by approximating PLE values through investigating the relationship between PLM variables and estimated distances.

Results are described in two sections. The first section represents outcomes of experimental analysis phase responsible for measuring the relation between optimal PLE and RSS values. The achieved goal of this phase is approximating values of PLE that fit within the navigation environments. The second section describes experimental analysis phase outcomes based on studying the relation between estimated distance and RSS, where distance computing depends on optimal PLE ranges.

4.2.1 Experimental analysis results for optimal PLE approximation

This experimental phase is responsible for PLE analysis, in which the relation between optimal PLE and values of RSS is analyzed. In addition, this phase explains how to choose optimal PLE of each RSS reading. Also, it describes how to choose optimal PLE ranges in two cases LOS and NLOS. The result depends on real-time experiments conduct in different time periods and environments as described earlier. Detail steps of this phase are explained as following:

4.2.1.1 Determining optimal Path Loss Exponent (PLE)

This step allows determining optimal values of PLE providing accurately estimated distance. Optimal PLE values were obtained by conducting an intersection point between reference distance values and linear equations representing the relation between achieved distances (approximate accurate distance) and path loss exponent values. PLE values considered in the initial experiments before PLE optimal approximation were between 2to 3 in LOS, and between 3 to 4 in NLOS.

Figures (4.4 to 4.9) below illustrate a sample of computed distances using initially measured PLE values at 5, 10 and 15 meters distance in both LOS and NLOS. The optimal PLE indicated by vertical line function intersecting the regression line.

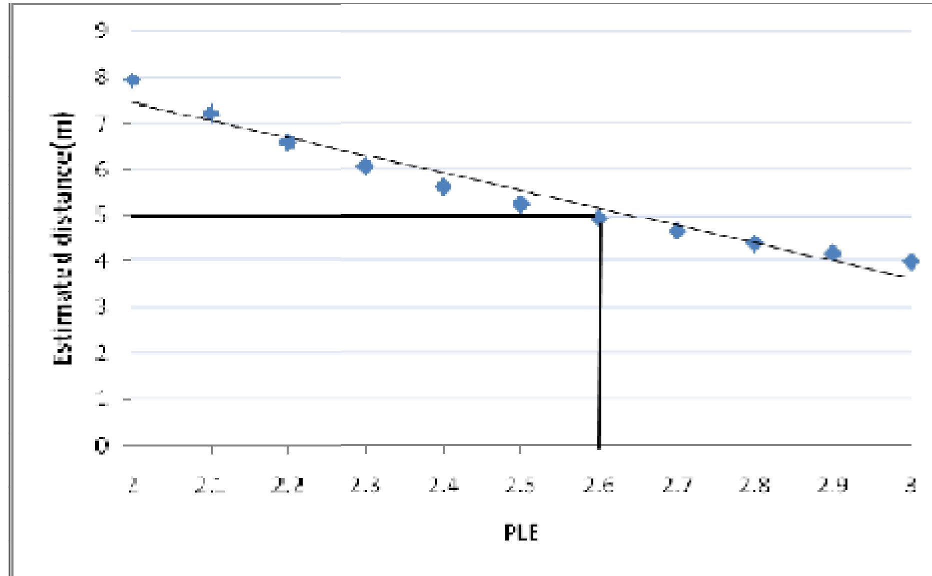


Figure 4.4

Distance estimated using PLE values at 5 meters in LOS

Figure 4.4 presents estimated distance in 5 meters in LOS case. The optimal PLE is 2.6 and accurately estimated distance is 5 meter

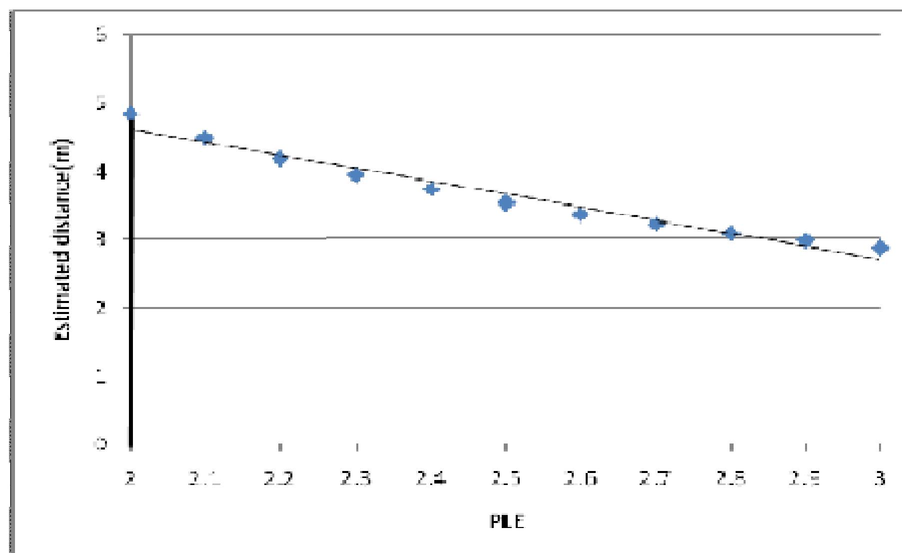


Figure 4.5

Distance estimated using PLE values at 10 meters in LOS

Figure 4.5 presents estimated distance in 5 meters in LOS case. The optimal PLE is 2 and accurately estimated distance using this value was 4.8~5 meter.

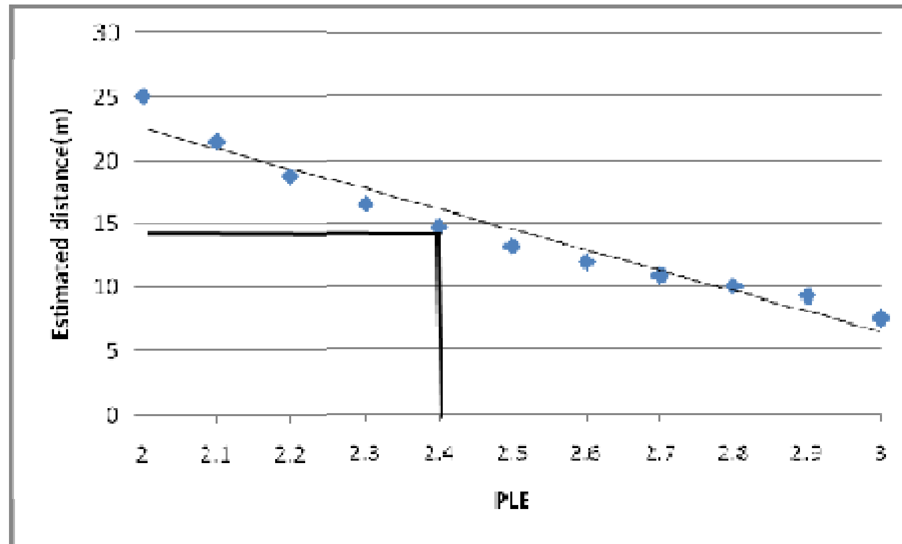


Figure 4.6

Distance estimated using PLE values at 15 meters in LOS

Figure 4.6 presents estimated distance at 15 meters in LOS case. The optimal PLE at this distance was 2.4 and accurate obtained estimated distance here is 14.8~15 meter

Figures 4.7, 4.8 and 4.9 show estimated distance using initial PLE values between the range 3 to 4 in NLOS environment.

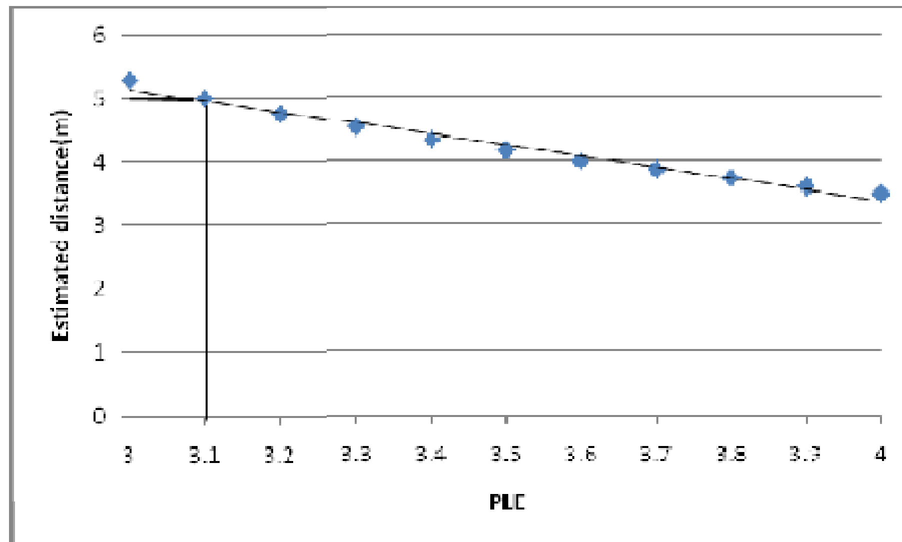


Figure 4.7

Distance estimated using PLE values at 5 meters in NLOS

Figure 4.7 shows estimated the distance at 5 meters, which optimal PLE at this destination is 3.1and the estimated distance is 5 meters.

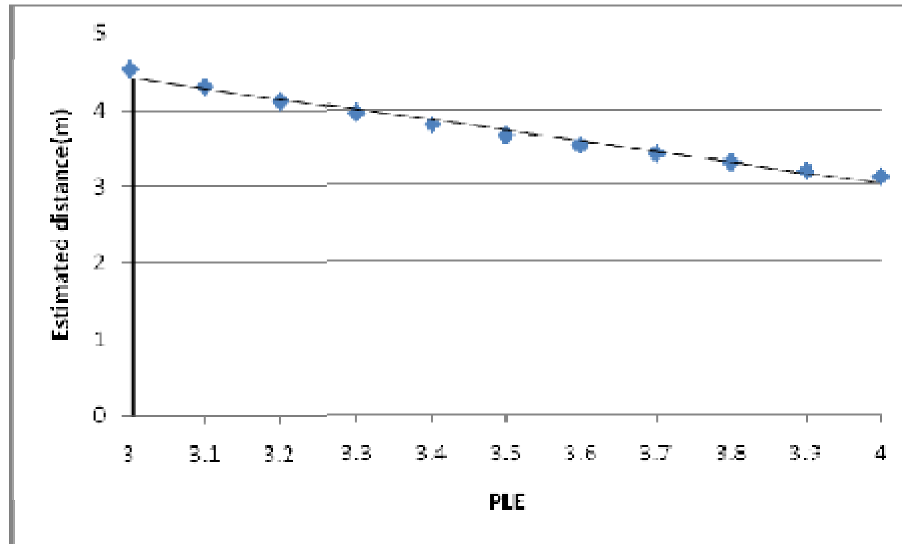


Figure 4.8
Distance estimated using PLE values at 10 meters in NLOS

Figure 4.8 describes measurements at 10 meters in NLOS case. The accurately estimated distance was 4.5~5 using optimal PLE of 3.

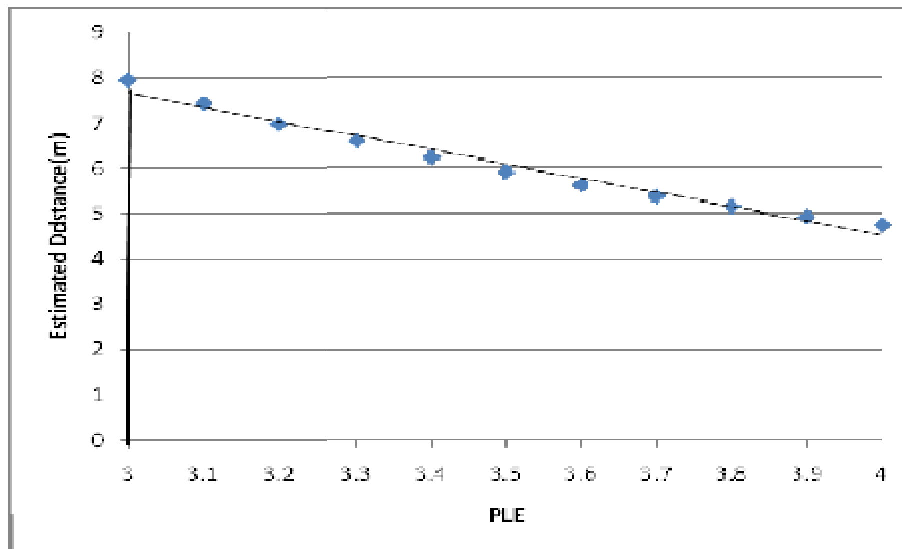


Figure 4.9
Distance estimated using PLE values at 15 meters in NLOS

In addition, Figure 4.9 presents measurements at 10 meters in NLOS case. The accurately estimated distance is 8 using optimal PLE is 3.

4.2.1.2 PLE relations analysis

After determining optimal PLE values for each meter considering values of RSS and accurate distances, the relation between optimal PLE values and each RSS value is analyzed using linear regression. Figures 4.10 and 4.11 describe relation between RSS and PLE using two different experimental samples in LOS environment.

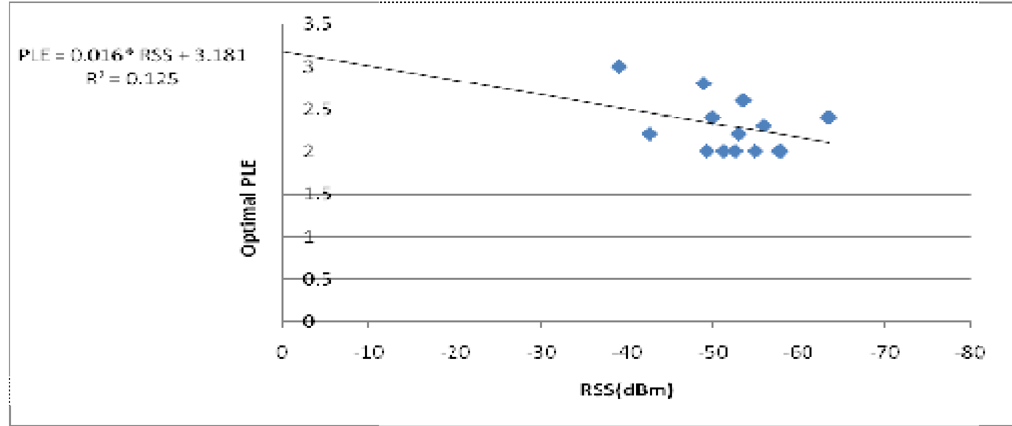


Figure 4.10

Regression between RSS and optimal PLE in LOS case using experimental sample 1.

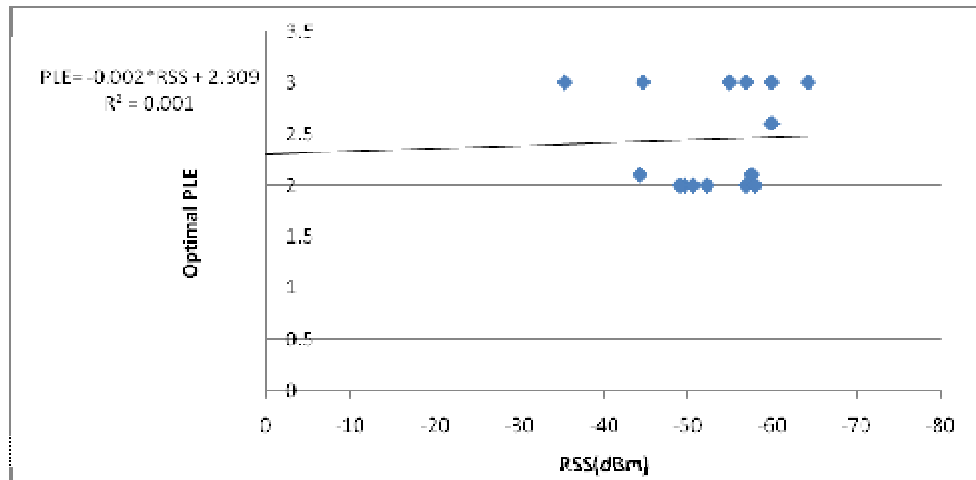


Figure 4.11

Regression between RSS and optimal PLE in LOS case using experimental sample 2.

Based on linear regression, relationship between PLE and RSS values is described in equations 4 and 5, using LOS experimental samples 1 and 2 respectively.

Equations are as following:

$$PLE = 0.016*RSS + 3.181 \quad (4)$$

$$PLE = -0.002 * RSS+ 2.309 \quad (5)$$

In equation 4, R^2 is 0.125 and for equation 5 R^2 is 0.001, this means the correlation is weak between optimal PLE and RSS.

Afterward, an additional linear regression for all experiments conducted in LOS environment is achieved in one regression equation, described in 6. The R^2 in this equation is 0.009. This overall regression is presented in Figure 4.12:

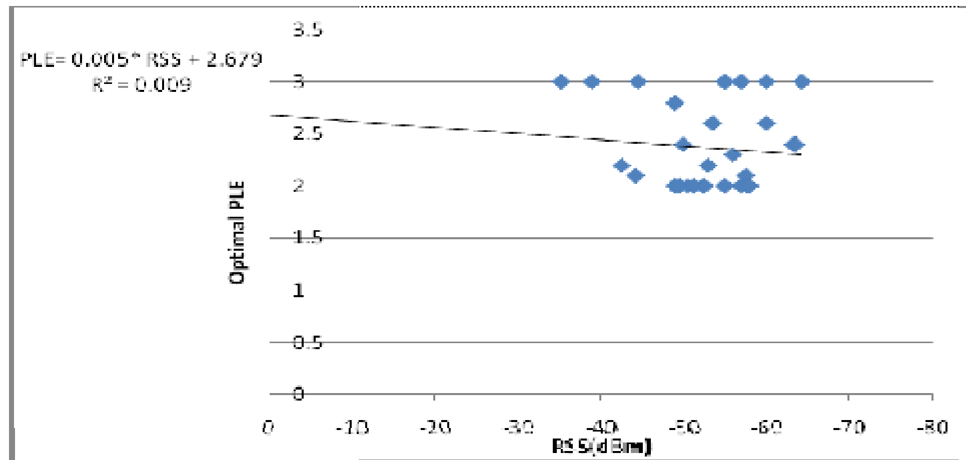


Figure 4.12

Linear regressions between RSS and optimal PLE in LOS for all experiments

$$PLE = 0.005*RSS + 2.679 \tag{6}$$

In addition, Figures 4.13 and 4.14 represents linear regression between RSS and optimal PLE using two different experimental samples within NLOS environment.

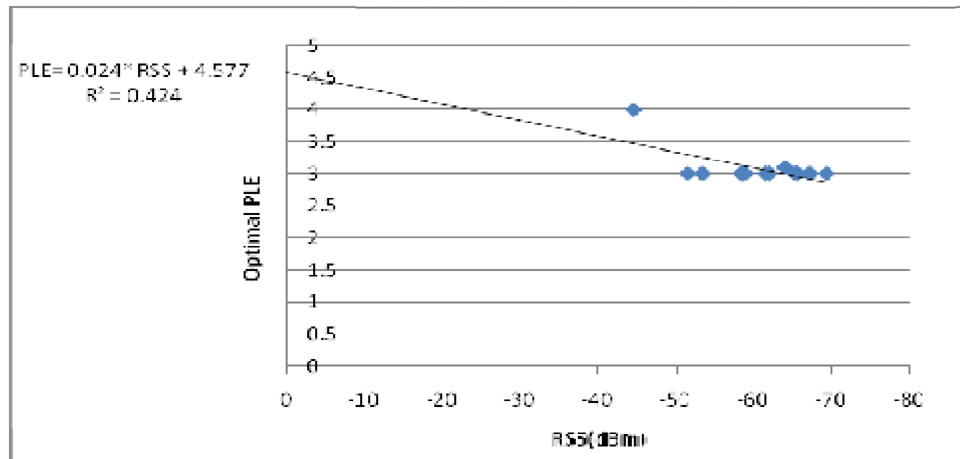


Figure 4.13

Regression between RSS and optimal PLE in NLOS case using experimental Sample 1

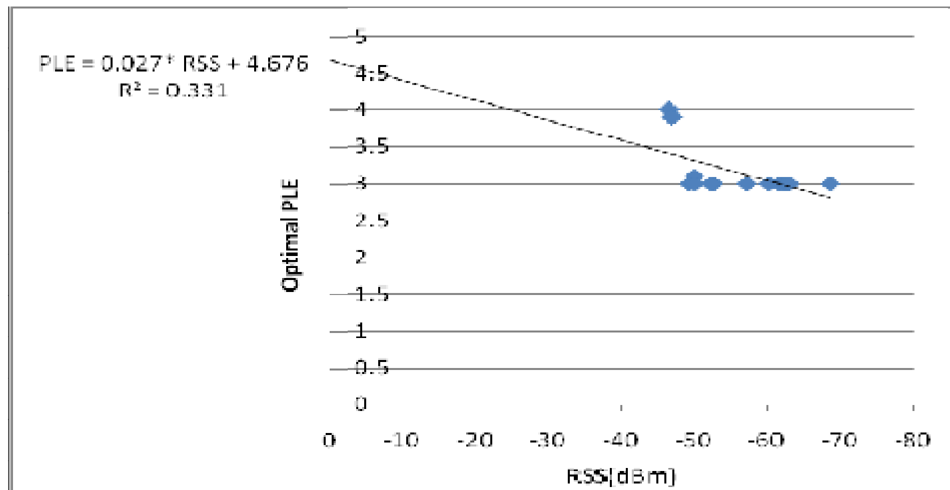


Figure 4.14
Regression between RSS and optimal PLE in NLOS case using experimental sample 2.

In contrast, equations 6 and 7 are two regression equations representing relation between optimal PLE and RSS values in NLOS using sample 1 and sample 2 of experiments respectively:

PLE= 0.024*RSS + 4.577 (7)
PLE = 0.027*RSS + 4.676 (8)

Where R^2 in equation 7 was 0.424, and in equation 8 it was 0.331. Hence, the correlation was not strong, however, better than in LOS case. Figure 4.15 represents linear regression all NLOS experiment samples in one regression equation.

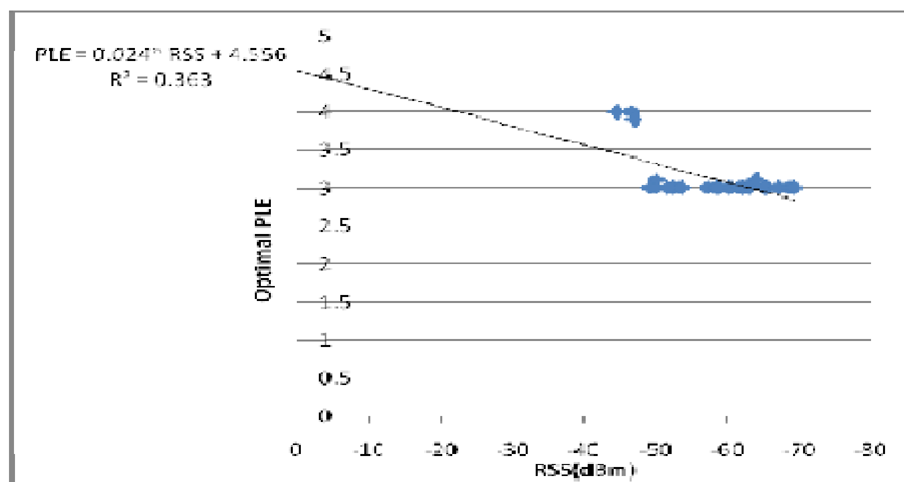


Figure 4.15
Linear regressions between RSS and optimal PLE in NLOS for all experiments

Linear equation for this overall regression is described in equation 9:

$$PLE = 0.024*RSS+ 4.556 \quad (9)$$

R^2 for this regression equation was 0.363.

Accordingly, the correlation in all equations at all environments is considered weak, because R^2 in all experiments was less than 0.5. Therefore, the RSS values and its relation with measured PLE cannot be used determine approximate optimal PLE values as required. However, results achieved in this section were used to choose an appropriate range of PLE values represents the radio signal propagation environments.

After studying and analyzing PLE parameter, estimating one optimal PLE value does not always give high distance accuracy. This is because RSS readings fluctuate due to multipath errors. Hence, using one fixed value for PLE within the environment is not the optimal solution. Figures 4.16 and 4.17 describe the difference between real distance and estimated distance use optimal PLE values in two cases LOS and NLOS.

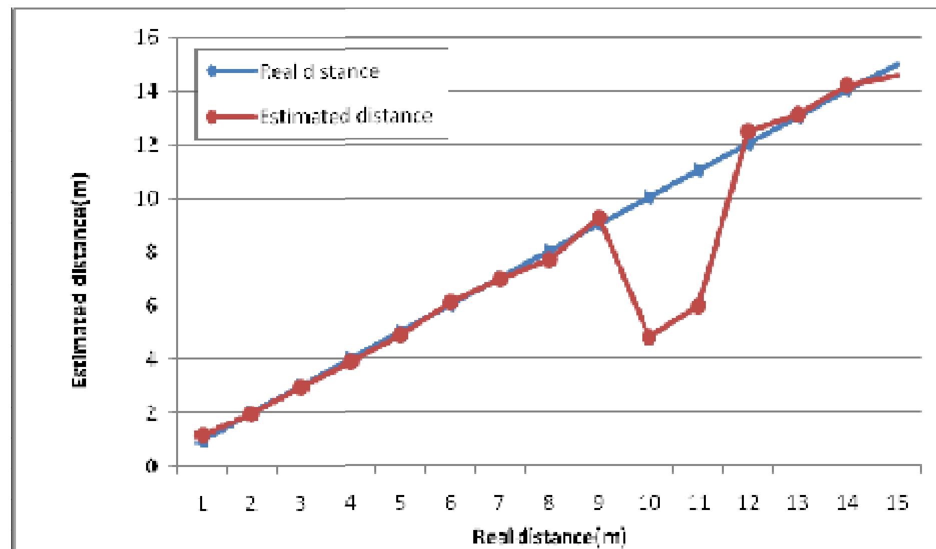


Figure 4.16

Difference between real distance and estimated distance using optimal PLE in LOS

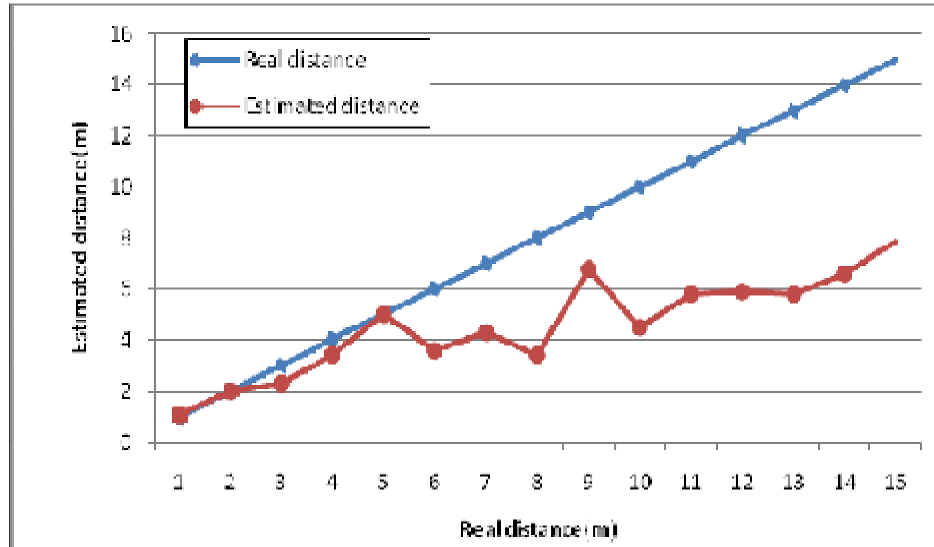


Figure 4.17
Difference between real distance and estimated distance using optimal PLE in NLOS

As illustrated in Figures 4.16 and 4.17 fluctuations exist in some values of estimated distance and real distance, Figure 4.16 describes estimated distance in LOS, and it is noted that distance variations are maximum at 10 m and 11m comparing to values. The reason was because RSS values at this distance were very affected by surrounding obstacles. The NLOS case presented in Figure 4.17 describes distance fluctuations. This was logical because of the difficult conditions available at NLOS environment. For example, no line of sight exists between transmitter and receiver making the signal to be more susceptible to attenuate in power or decays before reaching a receiver.

For this reason, additional experiments were conducted and results were used to determine optimal PLE ranges for more accurate distance estimation as described in the following section. This helped in reducing the effect of multipath and makes PLE values more adaptive to the environment.

4.2.1.3 PLE ranges analysis:

This step is responsible for finding ranges of optimal PLE values rather than using one value to represent each propagation environments. Optimal PLE values achieved from previous analysis phases are used to determine most frequent PLE values in two cases LOS and NLOS. After extensive analysis, it was confirmed that there are specific PLE values giving accurate distance estimation. Figures 4.18 and 4.19 illustrate optimal PLE ranges:

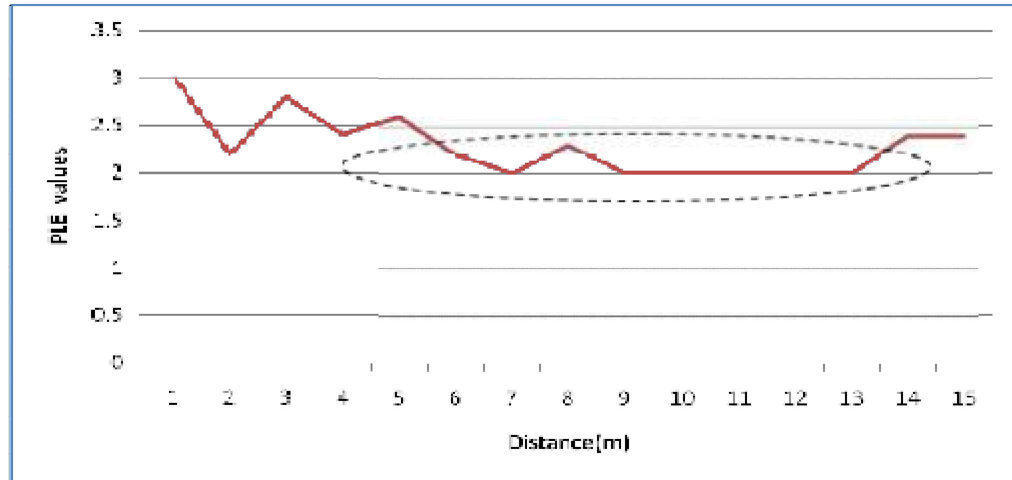


Figure 4.18
Ranges of PLE values in LOS

Figure 4.18 demonstrates most frequent values of PLE estimated in all experiments, Moreover, optimal ranges of PLE values in LOS were between 2 to 2.4, in which, this range gave the most accurate distances in all LOS experiments.

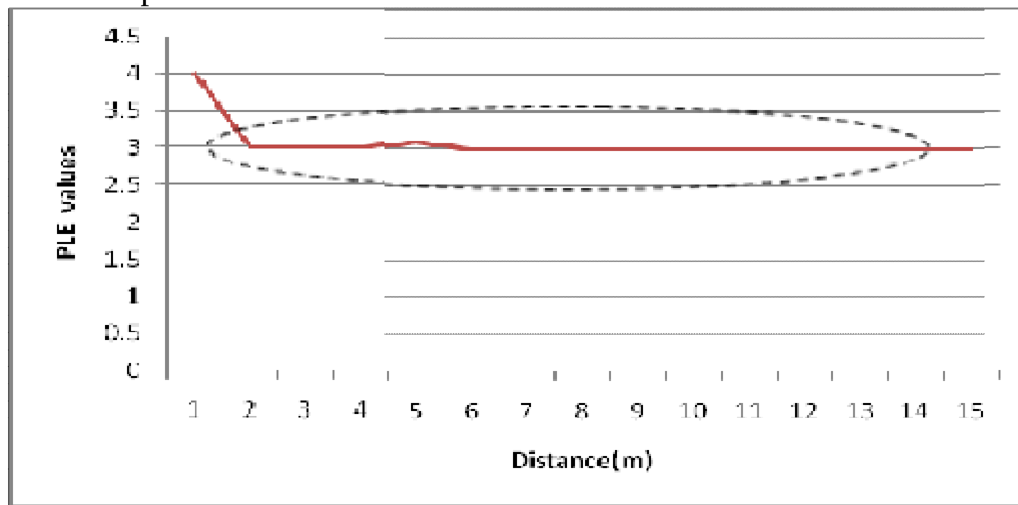


Figure 4.19
Range of PLE values in NLOS

In NLOS optimal PLE ranges was determined between from 2 to 3.3. A scan is noticed in Figure 4.19 most frequent PLE values were from 3 to 3.3. However, to improve estimated distance accuracy in NLOS case, values are decreased to reach optimal range from 2 to 3.3. An accuracy levels achieved in NLOS was below accuracy in LOS due to environmental conditions.

4.2.2 Experimental analysis results for optimal PLE ranges and RSS:

This analysis phase starts by analysis the relation between RSS and distance estimated. Figures 4.20 and 4.21 shows the strong linear relation between RSS and estimated distance in LOS for two different experimental samples, values of R^2 for linear regression relations shown in Figure 4.20 and 4.21 were 0.858 and 0.546 respectively.

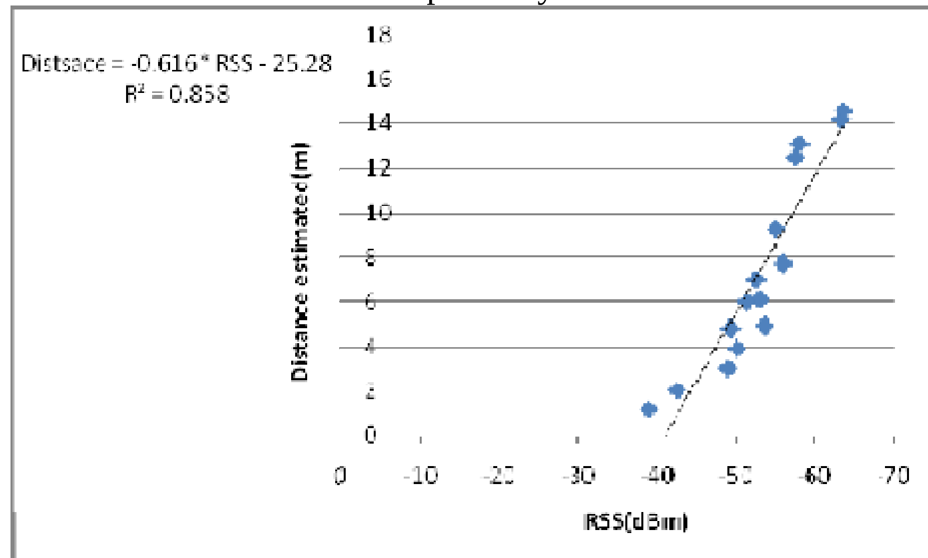


Figure 4.20

Linear regression between RSS and distance in LOS using experimental sample 1

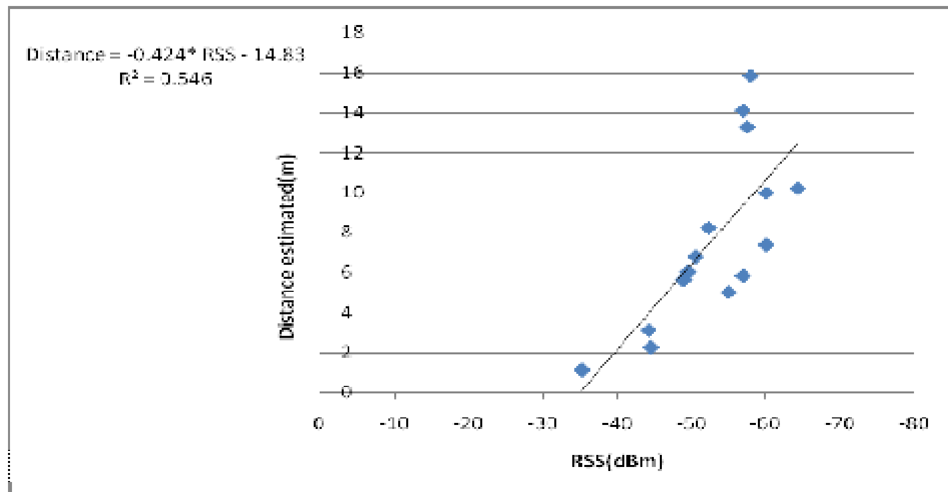


Figure 4.21

Linear regressions between RSS and distance in LOS using experimental sample 2

In addition, Figures 4.22 and the 4.23 shows the relation between average RSS readings and estimated distance in two different experimental

samples in NLOS case. Result describe the strong relation between RSS and estimated distance, in which R^2 in for the first sample described in Figure 4.22 was 0.929 and for the second sample described in Figure 4.23 it was0.959.

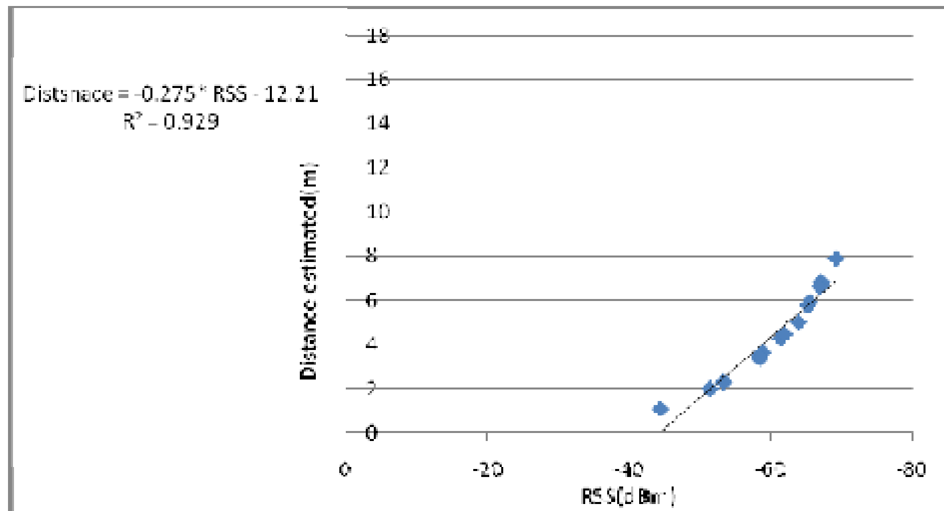


Figure 4.22
Linear regression between RSS and distance in NLOS using experimental sample 1

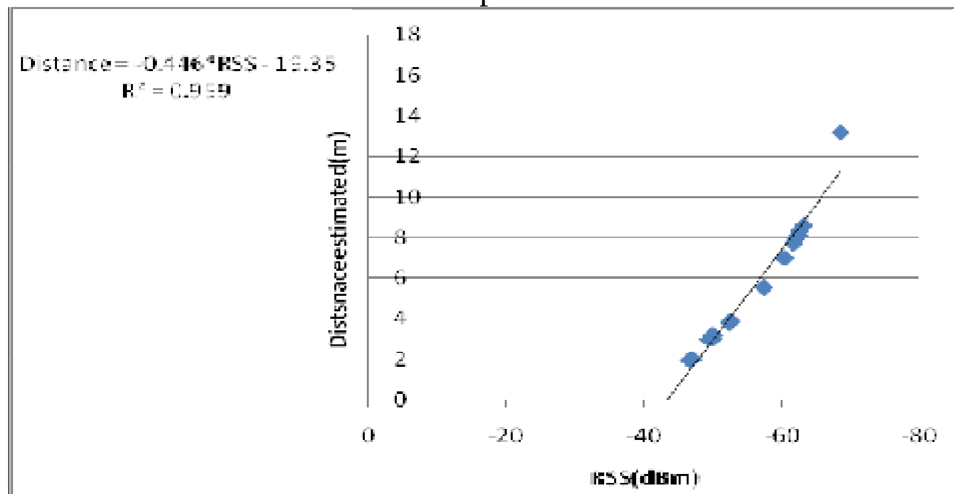


Figure 4.23
Linear regression between RSS and distance in NLOS using experimental sample 2

Correlation between RSS and estimated distance is very strong because the value of R^2 is more than 0.5 in all cases either in LOS and NLOS. This correlation confirms the capability of using RSS values to determine the distance between AP and mobile user. Hence, proposed

approach utilizes this relation to improving the accuracy of path loss model. This was conducted by using an average of RSS values achieved from previous distance step of the user. Afterward, newly computed RSS average is used in next step of the user. The average of RSS values in each step will make more consistency and adaptive use of RSS reducing fluctuations all readings.

4.2.3 Comparison analysis

This section provides a comparison between real distance values, conventional PLM distances, and distances achieved from proposed PLM variables approximation. As can be explained in chapter 3 the proposed approach used -65 RSS threshold to automatically distinguish between LOS and NLOS cases. If the average of RSS readings was less than -65, then LOS PLE range is used (2-2.4) to compute the distance. Otherwise, NLOSPLE range (2-3.3) is used to compute the distance.

The computed distance in conventional PLM depends on reading RSS values five times. Afterward, the average of five readings is applied to estimate the distance using PLE of 2 in LOS and 4 in NLOS.

To summarize, distance was estimated using proposed approach based on following steps:

1. Computing average of RSS readings in first place (initial step)
2. Compute the new average of RSS after removing outliers.
3. Compute distance using PLM and PLE ranges
4. Compute average of distance.
5. Compute average of RSS in second place (second step of the user) three times.
6. Remove outlier values of average RSS from previous and current steps.
7. Compute the new average of RSS in the current step.
8. Computing using optimal RSS and PLE ranges
9. Compute average of distances.
10. Repeat steps starting from step 5.

Comparison results were divided into two tables; Table 4.1 for distances measured at LOS and Table 4.2 for distances measured at NLOS. In addition, results describe the outcome of analyzing distances far from the access point. Distance analyzed starts from 16meters to 20meters.

Table 4.1
Distance Comparison in LOS

Real distance (meter)	Average RSS (dBm)	Distance estimated by Conventional PLM (meter)	Distance estimated by the Proposed approach (meter)
20	-59	7	12
19	-59	6	12
18	-58	11	11
17	-60	21	14
16	-57	13	9

Table 4.2
Distance estimated in NLOS

Real distance (meter)	Average RSS (dBm)	Distance estimated by Conventional PLM (meter)	Distance estimated by the Proposed approach (meter)
16	-73	4	16
17	-65	4	8
18	-68	4	11
19	-69	4	11
20	-65	4	7

As can be seen in Table 4.1 and 4.2 estimated distance using the proposed approach and optimal PLM parameters was improved in two cases LOS and NLOS. In addition, it is noted that values of RSS achieved are more compatible to each other, and no extreme values exist between average RSS.

4.2.4 Summery

This chapter describes the implementation of proposed functional approach using a set of experimental measurements and analysis phases. Results have highlighted how optimal PLE values are approximated for both NLOS and LOS navigation environments. Afterward, ranges of optimal PLE values were estimated. Experimental results analysis also describes how optimal RSS ranges are obtained and used to compute accurate distance values. The average RSS value in the previous move was used as an indicator to RSS in next user move. This provided consistency in RSS values estimation and reduces environmental effects.

Analysis results also confirmed that the estimated distance using proposed approach is accurate than the conventional approach. A statistical t-test was conducted to measure variance between distance computed using proposed approach and distance computed using conventional PLM model at a confidence level of 95%. T-test variance analysis shows a significant difference between distances, t-value was (3.5) for the variance between proposed approach computed distances and real distances. However, computed t-value was (19.7) for variance between conventional model computed distances. Tabulated-t was (2.13); hence, the difference was very significant in conventional model case.

4.3 Conclusions and future work

4.3.1 Conclusions

This work depicted a proposed useful approach utilized for Path Loss Models (PLM) parameters optimal estimation. The proposed useful approach has enhanced the usage of conventional path loss models including assessing PLM variables and distance calculation. This has permitted accomplishing propelled position accuracy and precision levels. A new assessment model was displayed and used to conduct continuous PLM variables estimations utilizing the proposed system inside all conceivable route situations, including LOS and NLOS.

Measured data was dissected accurately to portray the connection between PLE, RSS and distance. A feeble connection amongst RSS and PLE was affirmed. In any case, a solid connection was depicted amongst RSS and assessed distance. Utilizing these component connections and broad investigations of route environment have helped in giving ideal PLE and RSS ranges appropriate for high figured exactness in both LOS and NLOS.

Approximated ideal PLE range qualities were between 2 to 2.4 in LOS and 2 to 3.3 NLOS. Contingent upon solid connection amongst RSS and distance assessed ideal RSS qualities were evaluated. In which, normal of RSS and distance in the previous step were utilized to anticipate RSS esteem in the present step. This technique has made RSS values more consistency with other while the client is moving. What's more, this permits decreasing from vacillations in RSS readings that cause in light of the fact that multipath signal.

These ideal ranges of PLE and RSS were utilized to appraise the distance while the client is moving. The accomplished estimated distance was not extremely exact achieving centimeter level. However, an enhancement was accomplished comparing to traditional PLM either in LOS and NLOS conditions.

A t-test was carried out to determine the difference in distance estimation between proposed approach and traditional Path Loss model,

when the certainty level was 95%. However, the variance between distance estimated using proposed approach and real distance was (3.5), but between real distance and distance estimated using conventional path loss mode was (19.7). Tabulated-t was (2.13); therefore the difference was very significant in conventional model case.

4.3.2 Future work

The proposed approach will be implemented using trilateration techniques. This will allow utilizing proposed variables approximation process to determine location of mobile users using another distance estimation technique. In addition, to improve the position accuracy, the proposed approach will be developed to include additional source of distance using an integrated navigation sensor. This fused navigation solution will improve the efficiency of estimation initial user's step and next steps.

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Appendix (I)
Android code for read RSS of Wi-Fi signal

Android code for read RSS of Wi-Fi beacons access points

This appendix presents pseudo code and android code in order to scanning the access point. Thus, fetch the beacon frame to retrieve the values of Received Signal Strength (RSS) and MAC address from specific access point.

§ **Pseudo code**

- Scan of an access point holds the same Basic Service Set Identifiers (BSSID) in the code.

- Fetch the beacon frame to retrieve the Received Signal Strength (RSS) values.

§ **Android code**

```
class WiFiScanReceiver extends BroadcastReceiver}
  @Override
public void onReceive(Context c, Intent intent){
wifi= (WifiManager) getSystemService(Context.WIFI_SERVIC);
List<ScanResult> results1 = wifi.getScanResults();
                    if (wifi.isWifiEnabled()) == false
wifi.setWifiEnabled(true);
for (ScanResult result : results1){
MAC = result.BSSID;
                     RSS=result.level;
                    if(timer.getElapsedTimeMilli()<1000)
if(MAC.equals("00:19:e0:6e:d2:7a")){
txt1.setText("strength_signal" =RSS);}
}
                      }
```

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السنة: 2016